

# Demand Response eXchange in a Deregulated Environment

by

**Duy Thanh Nguyen, BEng(Hons)**

Submitted in fulfilment of the requirements for the Degree of  
Doctor of Philosophy



School of Engineering  
University of Tasmania

April 2012



## **Declaration of Originality**

This thesis contains no material which has been accepted for a degree or diploma by the University or any other institution, except by way of background information and duly acknowledged in the thesis. To the best of my knowledge and belief, this thesis contains no material previously published or written by another person except where due acknowledgement is made in the text of the thesis, nor does the thesis contain any material that infringes copyright.

Duy Thanh Nguyen

Date:

## **Statement of Authority to Access**

This thesis may be available for loan and limited copying in accordance with the Copyright Act 1986.

Duy Thanh Nguyen

Date:

# Preface

## Abstract

This thesis presents the development of a new and separate market for trading Demand Response (DR) in a deregulated power system. This market is termed Demand Response eXchange (DRX), in which DR in the form of hourly load reduction is considered a product to be negotiated between two groups of market participants, namely buyers and sellers. DR buyers, including all transmission companies (Transcos), distribution companies (Discos), and retail companies (Recos) need DR for their risk management benefits related to, for instance, transmission and distribution network security, and electricity market volatility. Sellers, including all Energy Service Companies (ESCOs), are capable of significantly modifying electricity customers demand to supply DR on request. The trading between these sellers and buyers is settled by a new system operator termed DRX operator (DRXO).

Two alternative market clearing schemes, namely pool-based and agent-based, are developed as the ground technical mechanism of a DRX. In the former scheme, all sellers and buyers are required to submit offers and bids reflecting their marginal costs and benefits, respectively, derived from a set of DR quantities. Based on this collected information, the DRXO will clear the market by centrally maximizing the total benefit for all participants under some economic constraints, i.e., demand-supply balance. In the other hand, in an agent-based scheme the participants are viewed as economic agents that behaves in a self-interested manner. The scheme will be designed to constrain each agent to ensure optimal global efficiency, while also allowing agents to maximize their own profits locally.

In order to evaluate these DRX schemes, we develop a comprehensive assessment framework using certain economic valuation methodologies such as cost-benefit analysis and externalities treatment. Firstly, DR cost and benefit for each participant in the market (i.e., buyers and sellers) are analysed in detail. Based on this local analysis, a global evaluation is performed to determine whether the optimized DR can give a positive social surplus. If so, the DR will be dispatched during the hour under consideration. Using this newly developed assessment framework, we demonstrate the advantages of DRX over conventional DR trading/scheduling schemes.

---

Throughout the thesis, both analytical proofs and numerical examples are provided to substantiate the advantages of the proposed DRX schemes. Our formulations rely on a wide range of theories: demand–supply modeling with a competitive market equilibrium, cost–benefit analysis, spot pricing of electricity, and network reliability assessment. Numerical simulations are performed on various test systems, including the Roy Billinton Test System (RBTS), to illustrate the effectiveness of DRX in analysing and optimizing DR benefits.

## Thesis outline

With reference to the DRX topics given above, the thesis is organized into six chapters. The following is a brief description of each chapter.

- Chapter 1 presents an introduction into the general research area of DR and overviews a range of challenges associated with scheduling the DR capacity. First, we discuss some unusual characteristics of electricity demand that entails a careful development of an electric power supply system. The status of this development to date is examined with a particular focus on issues related to power industry restructuring and deregulation. Then DR as a potential solution to these problems is introduced and its actual financial benefit estimated for the Australian national market. Finally, the proposed investigation into the crucial task of scheduling DR is outlined with a list of research topics to be presented in subsequent chapters.
- Chapter 2 introduces the novel concept of DRX and demonstrates its necessity as a new and separate market for trading DR. Here all the existing approaches to DR are classified and reviewed according to which electricity players (either Transcos, Discos, or Recos) are central to the analysis. The common limitations of these approaches motivates the development of a new and comprehensive scheme for scheduling DR. It is very interesting that such a scheme which considers DR benefits for all stakeholders turns out to be a new DR trading market—the DRX.
- Chapter 3 presents the design of a pool–based market clearing mechanism for DRX. First, we discuss the notions of economic pool and then pool–based market clearing, with illustrations based on examples relating to the wholesale electricity market. We then utilizes these concepts to develop a centralized optimization model used to clear the DRX market. This model has an objective function (i.e., maximizing total DR benefit for all players) and several economic constraints including: 1) demand–supply balance; and 2) the pricing of DR as a market product. Numerical simulation on a small power system are also performed to demonstrate the effectiveness of the proposed pool–based clearing mechanism.

- 
- Chapter 4 designs and evaluates an agent-based clearing mechanism as an alternative of the pool-based. As similar to Chapter 3, here we firstly introduces the concepts of economic agent followed by agent-based market clearing. We also explain the major advantages and drawbacks of an agent-based versus a pool-based schemes. Then a formal development, with the objective of achieving Pareto efficiency outcome given by a competitive market equilibrium point, is presented with numerous analytical proofs aiming to check the robustness of the proposed clearing approach. Case study is also given to substantiate this analysis.
  - Chapter 5 proposes a comprehensive assessment framework to rigorously analyse the costs and benefits derived from DR under either DRX or conventional DR scheduling and trading schemes. Several standard economic assessment methodologies are considered in this chapter to develop the proposed framework. Two sets of case studies, one on a small power system and the other on the well-known Roy Billinton Test System (RBTS), are then presented to illustrate the combined use of these methods for DR cost-benefit analysis and to demontsrate the advantage of DRX over existing DR schemes.
  - Chapter 6 finally summarises the major contributions of the thesis and suggests some directions for future studies aiming to extend the research work reported here.

To be concise, we do not present a single methodological chapter reviewing all concepts, theories, and techniques applied to our subsequent DRX analysis. Those methods will be distributed through the four main chapters where they actually employed.

The work outlined above was conducted from March 2009 to January 2012 at the School of Engineering, Univerity of Tasmania (UTAS). The candidate's research supervision was jointly provided by Prof. Michael Negnevitsky from UTAS and Dr. Martin de Groot from Commonwealth Scientific and Industrial Research Organisation (CSIRO). It is hoped that the thesis will be of interest and value to the potential readers whose task involves trading and/or scheduling DR capacity in deregulated power systems.

## Publications

The following is a list of journal and conference papers which have been produced as an outcome of the PhD candidate's research.

### *Journal articles*

1. D. T. Nguyen, M. Negnevitsky, M. de Groot, "Pool-based demand response exchange—Concept and Modeling," *IEEE Trans. Power Syst.*, vol. 26, no. 3, August 2011, pp. 1677–1685.

- 
2. D. T. Nguyen, M. Negnevitsky, M. de Groot, “Walrasian market clearing for demand response exchange,” *IEEE Trans. Power Syst.*, vol. 27, no. 1, February 2012.
  3. D. T. Nguyen, M. Negnevitsky, M. de Groot, “Modeling load recovery impact for arbitrage-free demand response applications,” *IEEE Trans. Power Syst.*, under review.

*Refereed conference papers*

1. D. T. Nguyen, M. Negnevitsky, M. de Groot, “Short-term valuation of electricity demand response,” in *Proc. IEEE PES General Meeting 2012*, pp. 1–8.
2. M. Negnevitsky, D. T. Nguyen, M. de Groot, “Load recovery in demand response scheduling,” in *Proc. IEEE PES General Meeting 2011*, pp. 1–8.
3. D. T. Nguyen, M. Negnevitsky, M. de Groot, “Pool-based demand response exchange—Concept and Modeling,” in *Proc. IEEE PES General Meeting 2011*, pp. 1–1.
4. M. Negnevitsky, D. T. Nguyen, M. de Groot, “An agent-based market-clearing scheme for the exchange of demand response,” in *Proc. IEEE PES General Meeting 2011*, pp. 1–6.
5. D. T. Nguyen, M. Negnevitsky, M. de Groot, “A new and separate market for demand response in restructured power systems,” in *Proc. IEEE PES 2011 Power Systems Conference and Exposition*, 20–23 March, pp. 1–7.
6. D. T. Nguyen, M. Negnevitsky, M. de Groot, “A comprehensive approach to demand response in restructured power systems,” in *Proc. AUPEC 2010 Conference*, 5–8 December, pp. 1–6.
7. M. Negnevitsky, D. T. Nguyen, and M. de Groot, “Novel Business Models for Demand Response Exchange,” in *Proc. IEEE PES General Meeting 2010*, pp. 1–6.
8. D. T. Nguyen, “Demand response for domestic and small business consumers: a new challenge,” in *Proc. IEEE PES T&D Conference and Exposition 2010*, pp. 1–7.
9. D. T. Nguyen, M. Negnevitsky, and M. de Groot, “Demand response in the retail market: Benefits and challenges,” in *Proc. AUPEC 2009 Conference*, 27–30 September, pp. 1–6.
10. D. T. Nguyen, M. Negnevitsky, D. Jiang, and M. de Groot, “A model of domestic energy management enabling low-cost technology,” in *Proc. AUPEC 2008 Conference*, 14–17 December, pp. 1–6.

# Acknowledgements

This thesis has only been possible with the supports from a great number of people. First, I would like to express my deep gratitude to my supervisor, Prof. Michael Negnevitsky, for his encouragement, patience, and belief in my abilities. He is simply a great mentor whose example knowledge and professionalism inspired me to working hard since the early days of my PhD. I am also deeply indebted to my co-supervisor, Dr Martin de Groot from CSIRO, for his continuous support and friendship over the last four years including the honours year of my undergraduate degree. His constructive comments contributed significantly to the quality of this research.

I thank all of my colleagues and friends, especially Dinh Hieu Nguyen, Phuong Nguyen, Ashan Latheef, Sushil Patil, Steffen Becker, Awak Mathok, Aman Bajracharya, Osman Haruni, and Polycarp Ifeanyi Muoka, with whom I have shared significant knowledge and experience during the course of my student life. A very special thank goes to Dr. Tien Ho for not only career orientation but also his numerous personal helps since the first day I arrived in Tasmania.

From the School of Engineering at UTAS, I would like to acknowledge all the academic staffs, especially Dr. David Lewis, Dr. Enamul Haque, Dr. Ameen Gargoom, and Dr. Jason Lavroff, for their technical suggestions over the years. I also appreciate the general staffs—Mary Dixon, James Lamont, Bernard Chenery, Steven Avery, and Russel Twinning, who particularly supported me with all necessary equipment and facilities for research. Special recognition goes to Max Fang and Justin Courtney for setting up the softwares to be used in my simulation work.

I wish to thank the CSIRO ICT Centre for giving me substantial supports technically and financially. Specific acknowledgement goes to Dr. Chen Wang for his valuable discussions on the demand-response research topics. I also appreciate Dr. Stephen Giugni who approved the PhD top-up scholarship and all financial expenses required for my conference travels.

Finally, none of this would be made possible without the endless love and unconditional supports of my parents—Duy Ngoc Nguyen and Thi Tuan Trinh, and my older brother—Duy Nguyen Nguyen, and my dear girl friend—Thuy Linh Nguyen. This thesis is dedicated to all of you.



# Contents

<b>Declaration</b>	<b>iii</b>
<b>Preface</b>	<b>iv</b>
<b>Acknowledgements</b>	<b>viii</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Electricity demand . . . . .	1
1.2 Power supply systems . . . . .	2
1.2.1 Restructuring and deregulation . . . . .	2
1.2.2 Power supply challenges . . . . .	5
1.3 Demand response . . . . .	9
1.3.1 On the DR concept . . . . .	9
1.3.2 Estimating DR capacity and its financial benefit . . . . .	11
1.3.3 Major challenges in scheduling DR . . . . .	12
1.4 Overview of the research . . . . .	13
1.4.1 The concept of demand response exchange . . . . .	13
1.4.2 Market clearing mechanisms . . . . .	14
1.4.3 Cost–benefit assessment framework . . . . .	15
<b>2 Literature Review and Demand Response eXchange</b>	<b>17</b>
2.1 Overview . . . . .	17
2.2 Existing approaches to DR . . . . .	18
2.2.1 Reco–based scheduling . . . . .	18
2.2.2 Transco–based scheduling . . . . .	20
2.2.3 Disco–based scheduling . . . . .	22
2.2.4 Common limitations . . . . .	23
2.2.5 Comprehensive DR scheduling requirements . . . . .	25
2.3 Proposed DRX approach . . . . .	25
2.3.1 Scope of the proposal . . . . .	25

2.3.2	On the DRX concept . . . . .	28
2.3.3	DRX models . . . . .	30
2.4	Practical implications of the DRX . . . . .	31
2.4.1	DR versus electricity . . . . .	31
2.4.2	DRX versus existing electricity markets . . . . .	32
2.4.3	Timescale . . . . .	34
2.4.4	Interactions between DRX and other markets . . . . .	34
2.5	Implementation . . . . .	35
2.6	Summary . . . . .	36
<b>3</b>	<b>Pool-based Market Clearing</b>	<b>38</b>
3.1	Overview . . . . .	38
3.2	Pool-based market concepts . . . . .	38
3.2.1	Economic pool . . . . .	38
3.2.2	Market clearing mechanisms . . . . .	41
3.3	Market clearing optimization model . . . . .	43
3.3.1	Overall description . . . . .	43
3.3.2	DR quantity and price as decision variables . . . . .	47
3.3.3	Objective function . . . . .	50
3.3.4	Constraints . . . . .	53
3.4	Numerical example . . . . .	56
3.4.1	Test system . . . . .	57
3.4.2	Assumptions on the supply and demand curves . . . . .	58
3.4.3	Modeling of partial DR approaches . . . . .	60
3.4.4	Analysis of the main results . . . . .	62
3.4.5	Discussion of other results . . . . .	65
3.5	Summary . . . . .	67
<b>4</b>	<b>Agent-based Market Clearing</b>	<b>71</b>
4.1	Overview . . . . .	71
4.2	Agent-based market concepts . . . . .	72
4.2.1	Economic agents . . . . .	72
4.2.2	Agent-based market clearing mechanisms . . . . .	74
4.3	Formulation of the market clearing problem . . . . .	78
4.3.1	Pareto efficiency . . . . .	78
4.3.2	Equivalent conditions . . . . .	81
4.3.3	Market equilibrium . . . . .	83
4.4	Walrasian auction design . . . . .	86

4.4.1	Overall design scheme . . . . .	86
4.4.2	Price adjustment methods . . . . .	86
4.5	Robustness evaluation . . . . .	90
4.5.1	Agent local optimization . . . . .	90
4.5.2	Convergence analysis . . . . .	92
4.6	Numerical simulation . . . . .	96
4.6.1	Test system . . . . .	96
4.6.2	Analysis of the market clearing results . . . . .	97
4.6.3	Convergence assessment . . . . .	98
4.6.4	Discussion . . . . .	100
4.7	Summary . . . . .	102
<b>5</b>	<b>Cost–Benefit Analysis and Treatment of Externalities</b>	<b>104</b>
5.1	Overview . . . . .	104
5.2	Common economic assessment methodologies . . . . .	105
5.2.1	Cost–benefit analysis . . . . .	105
5.2.2	Externality evaluation with public goods . . . . .	106
5.3	A novel framework for assessing financial DR benefits . . . . .	109
5.3.1	Trends in developing DR scheduling schemes . . . . .	109
5.3.2	Proposed framework . . . . .	112
5.4	In–market DR costs and benefits . . . . .	114
5.4.1	Customers . . . . .	114
5.4.2	The Transco . . . . .	117
5.4.3	Market–clearing . . . . .	121
5.5	Out–of–market surpluses . . . . .	122
5.5.1	Discos . . . . .	122
5.5.2	Recos and Gencos . . . . .	122
5.6	Numerical example . . . . .	123
5.6.1	Test system . . . . .	123
5.6.2	Evaluation results of the partial schemes . . . . .	126
5.6.3	Evaluation results of the DRX scheme . . . . .	129
5.7	RBTS case study . . . . .	133
5.7.1	The RBTS . . . . .	133
5.7.2	Estimating EENS . . . . .	133
5.7.3	Spot price analysis . . . . .	135
5.7.4	Clearing the DRX market . . . . .	137
5.7.5	Computational issues . . . . .	138
5.8	Conclusion . . . . .	139

<b>6</b>	<b>Conclusion and Future Studies</b>	<b>142</b>
6.1	Thesis summary . . . . .	142
6.2	Major contributions . . . . .	145
6.2.1	Constructing a public view of DR . . . . .	145
6.2.2	The DRX concept . . . . .	146
6.2.3	Market clearing mechanisms . . . . .	146
6.2.4	Comprehensive cost–benefit assessment . . . . .	147
6.3	Suggestion for future research . . . . .	147
6.3.1	Modeling of dynamic load recovery . . . . .	147
6.3.2	DR price volatility . . . . .	148
6.3.3	Non–convexities . . . . .	148
6.3.4	Game–theoretic analysis . . . . .	149
6.3.5	Long term impact assessment . . . . .	150

# List of Figures

1.1	Power system structures: (a) Integrated; (b) Competition; (c) Competition with ESCos. Note: a Transco is sometimes called transmission system operator (TSO), a Reco called retailer, a Disco called distributor, and an ESCo called aggregator. . . . .	3
1.2	Blackout frequencies in the United State [15]. Note: during each year, blackouts are clas- sified based on their size that is the number of customers being disconnected. Each size is assigned with a color. For example, the color for the size over 4,000,000 customers is black. . . . .	6
1.3	Spot price volatility in NEM during the period from 1-Jan-2009 to 31-Jan-2009 [18]. Note: unit of the left vertical axis is MWh, while unit of the right axis is \$/MWh. . . . .	7
1.4	Comparison between the growth in peak demand and the growth in generation capacity during the period 1996-2000 within the California state and within the entire Western States Coordinating Council (WSCC) region [21]. . . . .	9
2.1	A sample of hourly generation bidding prices in NEM, showing the potential impact of relative small demand reduction on spot price [27] . . . . .	19
2.2	Using DR to reduce electricity demand following transmission capacity limit . . . . .	21
2.3	Circling different types of DR scheduling approaches . . . . .	24
2.4	Demand Response eXchange . . . . .	29
2.5	Fundamental models for DRX: (a) Bilateral; (b) Pool-based . . . . .	31
2.6	Modified power system structure with: (a) pool-based DRX model; (b) Bilateral DRX model . . . . .	32
2.7	A conceptual illustration of smart grid [69] . . . . .	35
3.1	Electricity pool . . . . .	39
3.2	(a) Real time fluctuations of generation and load; (b) Imbalances resulting from these fluctuations . . . . .	42
3.3	Flowchart for clearing a DRX market . . . . .	44
3.4	Verifying DR dispatch by a customer . . . . .	46
3.5	Small power system for demonstrating customers aggregation. Here each feeder load point (1, 2,...,14) supplies power for a small geographical area such as suburbs . . . . .	48
3.6	Market clearing model . . . . .	51

3.7	The test system . . . . .	57
3.8	Load curtailment (in MWh on the right axis) versus customer willingness (on left axis with no unit). Note: the horizontal axis represents customer index . . . . .	63
3.9	Net benefit (on the right axis) versus load curtailment (on the left axis). Here the horizontal axis represents customer index . . . . .	64
3.10	The relationship of DR market clearing prices, quantities purchased, gross benefit for the Disco (the results here are normalized by the corresponding peak values.) . . . . .	65
4.1	Agent with a local view into the world . . . . .	72
4.2	Structures of an agent-based market clearing system. Here the lines represent links . . .	75
4.3	Pareto efficiency for a two-agent market . . . . .	79
4.4	Assumptions on cost and benefit functions . . . . .	83
4.5	Equilibriums in different types of market . . . . .	84
4.6	The proposed multi-round market clearing mechanism . . . . .	87
4.7	Small power system for demonstrating the Newton pricing method. Here each feeder load point (1, 2,...,5) supplies power for a small geographical area such as suburbs . . . . .	89
4.8	Convexification as an approximation tool . . . . .	92
4.9	The test system . . . . .	96
4.10	The convergence rate $\ \mathbf{I} + \mathbf{KJ}^*\ $ versus the adjustment factor $\mathbf{K}$ . . . . .	98
4.11	Classical tâtonnement for different $\mathbf{K}$ . . . . .	98
4.12	Convergence of the classical tâtonnement with different starting points . . . . .	99
4.13	Illustrating the online estimation of inverse Jacobian matrix . . . . .	99
4.14	Newton tâtonnement with various ranges of estimation error . . . . .	101
4.15	Newton tâtonnement via finite-difference online estimation of $\mathbf{J}^t$ . . . . .	101
5.1	The whole assessment procedure . . . . .	108
5.2	Flow chart of the framework for assessing DR costs and benefits . . . . .	113
5.3	Benefits for consumer . . . . .	115
5.4	DR supply curve . . . . .	117
5.5	Costs to the Transco . . . . .	118
5.6	DR demand curve . . . . .	120
5.7	The 4-bus test system . . . . .	124
5.8	Spot price estimation curve . . . . .	125
5.9	EENS estimation in the transmission network (Note: To simplify the illustration, each curve represents load reduction for providing DR at the corresponding bus subject to unchanged load at the other bus). . . . .	125
5.10	Transmission level of the RBTS [118] . . . . .	132
5.11	Full diagram of the RBTS [119] . . . . .	132
5.12	Sensitivity-based EENS estimation at the RBTS's transmission level . . . . .	133

5.13	Effect of the outages on spot price . . . . .	136
5.14	Illustration of the price estimation . . . . .	136
5.15	DR surpluses under the DRX market-clearing scheme . . . . .	138

# List of Tables

1.1	Problems in a restructured power system . . . . .	5
1.2	DR capacities in some countries . . . . .	11
1.3	Annual estimate of financial DR benefits in NEM . . . . .	12
2.1	Summary of existing DR research . . . . .	18
2.2	Some large ESCOs . . . . .	27
2.3	List of markets within a restructured power system . . . . .	33
3.1	Examples of market clearing . . . . .	41
3.2	Some well-developed AMI standards . . . . .	47
3.3	Grouping customers under each DR buyer . . . . .	57
3.4	Customer types . . . . .	59
3.5	Valuation coefficients . . . . .	60
3.6	Partial DR models . . . . .	62
3.7	Comparative net benefit (\$) . . . . .	62
3.8	Comparative DR quantities (MW) and payments(\$) . . . . .	62
3.9	The impact of contribution rates vector on DRX outcome . . . . .	66
4.1	Types of agents . . . . .	73
4.2	Pool-based versus agent-based market clearing models . . . . .	77
4.3	Comparative results . . . . .	97
5.1	Examples of cost–benefit analysis . . . . .	105
5.2	Examples of externality . . . . .	107
5.3	Private goods versus public goods . . . . .	107
5.4	Characteristics of DR scheduling schemes . . . . .	112
5.5	Retail prices . . . . .	126
5.6	Customer elasticity . . . . .	126
5.7	Market clearing under the Transco-based scheme . . . . .	127
5.8	Out-of-market surpluses under the Transco-based scheme . . . . .	127
5.9	Market clearing under the Reco-based scheme . . . . .	128



5.10	Out-of-market surpluses under the Reco-based scheme . . . . .	128
5.11	In-market surpluses (\$) in the DRX . . . . .	130
5.12	In-market payments (\$) and DR quantities (MWh) in the DRX . . . . .	130
5.13	MAPE of EENS estimation with 0 – 0.1 p.u. load reductions . . . . .	134
5.14	MAPE of EENS estimation with 0 – 0.5 p.u. load reductions . . . . .	134

# List of symbols

Here is a list of key symbols to be used in our DR models and methods. The other symbols will be introduced within texts where they first appear.

## Indices

$l$	Customer index.
$i$	DR seller index (i.e., ESCo).
$n$	Customer group index.
$j$	DR buyer index (i.e., Transcos, Recos, and Discos).

## Sets

$\mathcal{L}_i$	The set of all customers represented by ESCo $i$ as a DR buyer.
$\mathcal{I}$	The set of all DR buyers in the market.
$\mathcal{N}_j$	The set of all customer groups providing DR to a seller $j$ .
$\mathcal{J}$	The set of all DR buyers in the market.

## Functions

$C_i$	Cost of producing DR by ESCo/seller $i$ on behalf of customers.
$B_j$	Benefit of utilizing DR by buyer $j$ .

## Paramaters

$a_i, b_i, \theta_{i,l}$	Coefficients included in the cost function, $C_i$ .
$\alpha_{j,n}, \beta_{j,n}$	Coefficients included in the benefit function, $B_j$ .

## Decision variables

$x_{i,l}$	Individual DR quantity provided by customer $l$ under ESCo/seller $i$ .
$c_{i,l}$	Marginal cost associated with producing $x_{i,l}$ .
$y_{j,n}$	Aggregated DR quantity provided to buyer $j$ from customer group $n$ .
$p_{j,n}$	Price of $y_{j,n}$ , offered by the buyer for DR.

# List of abbreviations and acronyms

Here is a list of major abbreviations and acronyms to be used throughout the thesis. Others will be introduced within texts where they first appear.

Disco	Power distribution company (also called distribution system operator—DSO)
DR	Demand response
DRX	Demand response exchange
DRXO	Demand response exchange operator
EENS	Expected energy not supplied
ESCo	Energy service company
Genco	Power generation company (also called generator)
HAN	Home area network
ISO	Independent system operator
KKT	Karush–Kuhn–Tucker
MO	Market operator
NEM	National electricity market (in Australia)
RBTS	Roy Billinton test system
REC	Renewable energy certificate
Reco	Electricity retail company (also called retailer)
Transco	Power Transmission company (also called transmission system operator—TSO)
U.S.A	The United States of America
VoLL	Value of lost load

# Chapter 1

## Introduction

### 1.1 Electricity demand

Electricity is a particular form of energy that can be produced from various sources such as hydro, thermal, nuclear and renewable energy. Bulk electricity is often delivered over a very long distance for being consumed by the end-use customers in their daily activities. The electricity consumption is given by a real-time physical process in which the customers convert the electrical energy into other forms of energy used to run domestic appliances (i.e., hot water, air conditioner) or industrial loads (such as electric motors). This energy conversion process is simple to such an extent that it can be adapted by almost everybody for their own consuming purposes. Indeed, this convenience makes electricity the major energy resource utilized by end users during the course of their life [1].

Being an important resource, electricity can be treated as a “commodity” to be traded between the customers and a utility company who is going to produce it [2]. In this trading context, the utility provides the customers with a right amount of electricity they require in each time period (i.e., hour-ahead). This amount, which can be easily measured via meter reading, is referred in microeconomics as electricity demand. In this sense, consumers of electricity, like consumers of all other commodities, tend to increase their demand up to the point where the benefit they derive from electricity consumption is equal to the cost they have to pay [1,3–5]. In particular, a manufacturer will not produce widgets if the cost of electricity required to produce these widgets undermines their selling profit. Similarly, a small business (i.e., restaurants, shopping centers) will never increase the lighting level beyond the point where the additional electricity consumption cost is still compatible with the additional benefit associated with attracting more clients [1].

#### **Specific characteristics of electricity demand**

Despite having many similar properties with other types of commodities, the electricity itself possesses some unusual characteristics, making it hard to deliver from the utility to

end-use customers following their demand [6]. First, electricity is difficult to store in bulk, which can be explained by the inherent limitations of the current storage technologies (for instance, requiring high capital cost but offering low operational efficiency). This physical characteristic is further demonstrated by the fact that the global storage capacity (all over the world) makes up only 3% of electricity production capacity, and such a situation will certainly not change in the near future [7]. Low storage capacity implicates that electricity must be consumed as it is generated. Additionally, the electricity delivery from a utility to its customers must be a real-time process functioning much faster than any other delivery system (i.e., for gas, oil, and other types of energy).

Second, electricity demand is relatively inelastic with the market price, meaning that the customers would not alter their consumption significantly in response to a short-term variation in the price they have to pay. The inelasticity of electricity demand can be explained by two economic and social reasons [6]. From an economic perspective, the cost of using electrical energy accounts for only a small portion of the total production cost for most industrial goods. It also represents only a minor fraction of the living cost spent by households. At the same time, the electricity benefit is indispensable in any manufacturing process and is considered to be vital for most individuals in an industrialized society. Therefore, most industrial customers will preferably not reduce their production to avoid only a small increase in their electricity payments (as the savings in short term may be more than offset by the loss of production profit). Similarly, households will probably not reduce their comfort to cut their electricity bill by only a few percents. The second reason for demand inelasticity is historical. Since the beginning days of commercial electricity generation (i.e., over a century ago), electricity has been marketed as a commodity that is easy-to-use and always available. This convenience has resulted in a custom that very few people perform an economic analysis each time they turn on the appliances [1].

Due to its unusual characteristics, short-term electricity demand is hard to change and therefore must be served instantly by the utility under any condition. This delivery task is discussed in the next section via the development of an electricity supply system.

## **1.2 Power supply systems**

### **1.2.1 Restructuring and deregulation**

In traditional sense, an electric power supply system (or simply called power system) is a physical network of electrical components (i.e., generating units, transformers, transmission lines, circuit breakers, and relays) which are used to produce and delivery electricity to end-use customers. When the power systems were established, they included the electricity generation, transmission, and distribution monopolized by local utilities. However,

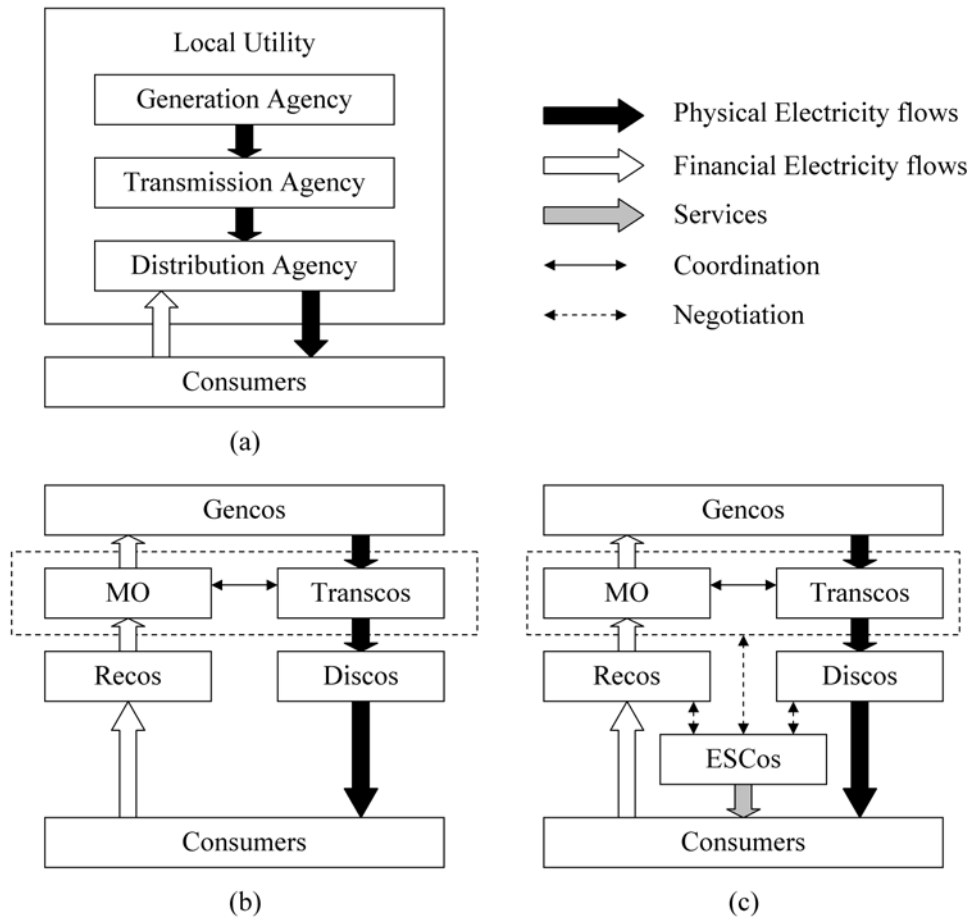


Figure 1.1: Power system structures: (a) Integrated; (b) Competition; (c) Competition with ESCos. Note: a Transco is sometimes called transmission system operator (TSO), a Reco called retailer, a Disco called distributor, and an ESCo called aggregator.

for the last two decades, power system restructuring and deregulation has been underway in many countries around the world. The main driver for this change is, as similar to other industries, the perceived need for introducing competition in generation and retailing, and thereby, reducing inefficiencies, lowering operational costs, and increasing customer choice in electricity supply [3–5, 8–12].

As a result of restructuring and deregulation, local utilities have been broken up into a number of independent stakeholders, which includes generation companies (Gencos), transmission companies (Transcos), distribution companies (Discos), retail companies (Recos), and energy service companies (ESCos). The operations of these power companies are under a supervision of some government delegates such as the regulator, the market operator (MO), and the independent system operator (ISO).

Fig. 1.1 shows three consecutive structures of a power system involving the above electricity sector players. These are integrated structure, competition structure, and the competition structure with ESCos, which correspond to three major steps of restructuring

from the beginning to the current state. Before describing these structures, we should make it clear as follows. First, the restructuring is underway in many developed countries such as Australia, U.S. and U.K. The consideration for power systems situation in developing countries is beyond the scope of this thesis. Second, the structures as will be described reflect the operations of power systems on day-ahead and real-time timescales only.

The integrated structure shown in Fig. 1.1–(a) refers to the electricity generation, transmission, and distribution monopolized by a local utility within a well-bounded geographical area (i.e., states, provinces). Sometimes, such an utility is called a vertically integrated utility. As one can be see, the utility is constituted of three operational departments, namely generation department, transmission department and distribution department. Their functionalities are given as follows. The generation department is responsible for operating all utility owned generators and submitting the amounts of generation outputs to transmission department. The transmission department is responsible for operating the transmission network, maintaining the network security and reporting outages to other departments. The distribution department is responsible for operating distribution networks and selling electricity to consumers. One of the main characteristics of the integrated structure is that there is no trading/negotiation between these internal departments. Additionally, the utility plays the role of being a monopoly electricity supplier for consumers within the given geographical area.

The competition structure shown in Fig. 1.1–(b) refers to the partition of a vertically integrated utility into various independent players including Gencos, Transcos, Discos and Recos, whose operations are under the supervision of a MO and a ISO. There are two major operational domains in this structure, namely market domain and network domain. Within the wholesale market, Gencos make bids to supply electricity at chosen prices. The MO receives the Genco bids, ranks them according to bid price and accepts enough bids to satisfy the forecasted demand plus a safety margin. Recos buy bulk electricity from the wholesale market at spot prices and sell retail electricity to their customers at generally fixed prices. Under retail competition, consumers are allowed to change Recos when they are offered a lower retail price. In the network domain, Transcos are primarily responsible for operating, and also maintaining the security of, transmission network. The Transcos are not involved in the clearing of electricity market and its role in generation scheduling is limited to ensuring that the submitted schedules are within a transmission network security margin. Besides the Transcos, players involved in network operations are Discos. They are responsible for managing their own distribution networks consisting of radial feeders connected through substations to the transmission network.

One of the main characteristics of the competition structure of a power system is that consumers are always treated as ‘dumb loads’ to be forecasted and served under all system conditions. Balancing generation and load is done almost entirely through actions taken by

the MO and Transcos. As a result, consumers have very limited opportunity to participate in the electricity market. This has been seen as one of the prime reasons for causing both spot price spikes in wholesale markets and supply outages in transmission and distribution networks [13].

The final structure shown in Fig. 1.1–(c) is generally similar to the competition structure except for the ESCos participation. ESCo is an independent agent providing its customers with a wide range of innovative services including bill management, home management, home electricity generation, and other services [14]. Based on these service provisions, the ESCo aggregates its customers into a single purchasing unit to negotiate the purchase of electricity from Recos. ESCos also negotiates demand response (DR) and home generation, on behalf of their customers, with Recos, Discos, and Transcos. Many economists believe that the participation of ESCos with innovative services and consumer aggregations can offers potential solutions for small-scale consumers to effectively manage their consumption, and thereby becoming active participants in the electricity market [12–14].

### 1.2.2 Power supply challenges

The restructuring through deregulation has introduced competition to the power system via the creation of wholesale and retail electricity markets. Unfortunately, this competition results in a new set of challenging problems associated with maintaining a reliable and economical power supply [12]. These problems can be categorized as network based and market based, both related to the rapid growth in electricity peak demand (See Table 1.1).

Table 1.1: Problems in a restructured power system

Catergories	Problems
Network security	Blackouts
	Generation–load imbalances, transmission line overloads
	Voltage and frequencies instability
Market volatility	Crisis
	Volatile spot prices, flat retail prices
	Limited demand–side participation, market power
	Externalities
Rapid demand growth	Outstrip the growth in supply capacity

#### Network security

The network security problems arise as the electricity is inextricably linked with a physical power network that functions much faster than any other market. In this physical system, supply and demand—generation and load—must be balanced on a second-by-second basis. If this balance is not maintained, the system will collapse with catastrophic



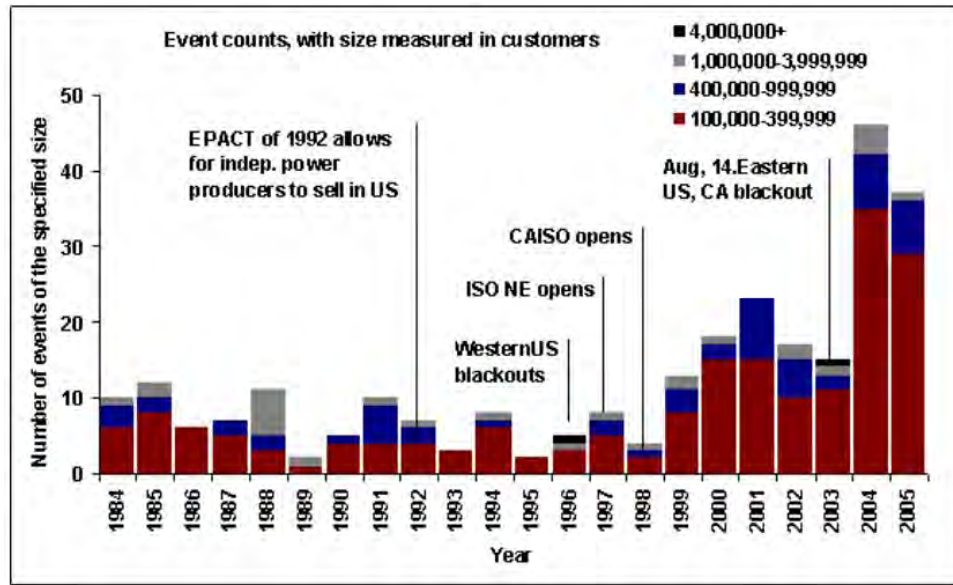


Figure 1.2: Blackout frequencies in the United State [15]. Note: during each year, blackouts are classified based on their size that is the number of customers being disconnected. Each size is assigned with a color. For example, the color for the size over 4,000,000 customers is black.

consequences. Such a system blackout is intolerable as it is not only the trading system that stops working but also an entire region or country that may be without power for many hours. Restoring a power system to normal operation following a wide blackout is a very complex process that may take 24 hours or more in a large region [6]. This problem incurs significant economic and social losses to customers.

Fig. 1.2 shows the frequency (measured in times per year) of blackouts in the United States during the period 1994–2005. As can be seen from the chart, the frequency increased significantly from year 1999 to year 2005, and peaked during year 2004. While this case is very complex, one of the main reasons for this increasing trend is the lack of network investments under restructuring during the same time period [16]. This problem is explained by the following.

In the old days, investments in network infrastructures were determined by consensus between the vertical utility and its regulator, and the approved investments were then funded by the government. This is, however, not the case under restructuring. Since the power system has been unbundled, each network in it (i.e., transmission, distribution) is operated by an independent company such as Transcos and Discos. These players would automatically make the needed investments in hopes of profiting from them by charging those electricity traders (i.e., Gencos, Recos) who use the networks. Unfortunately, network usage charges during the 1990s had still been under government control, and thus, they were not attractive enough to the network companies. In other words, the charging fees give the companies very little incentive for updating their own networks.

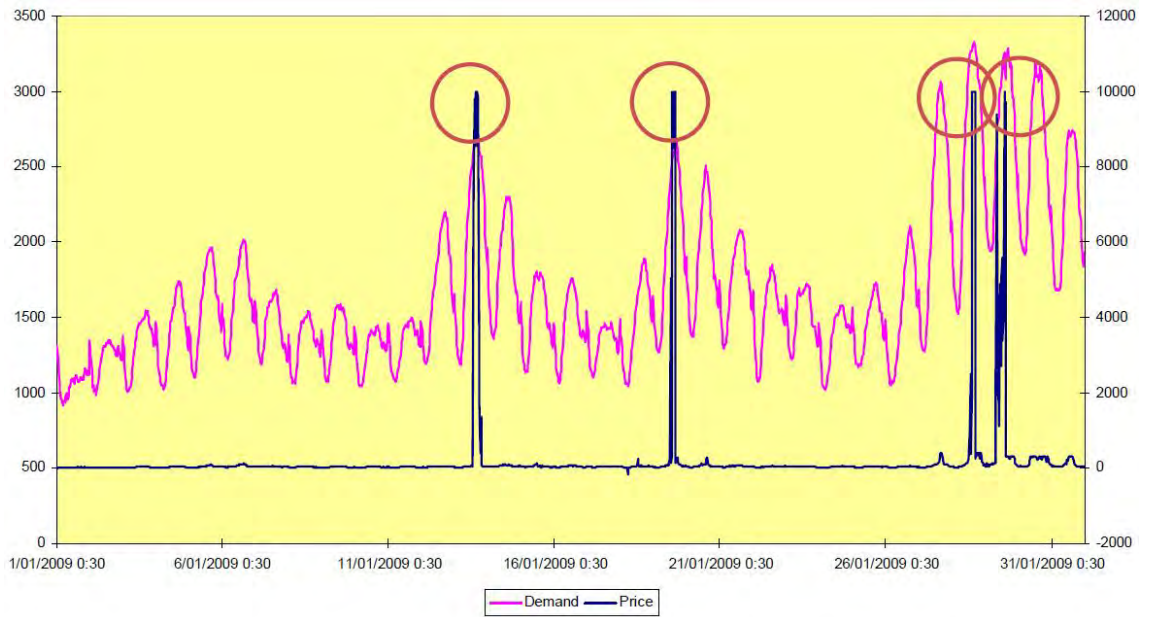


Figure 1.3: Spot price volatility in NEM during the period from 1-Jan-2009 to 31-Jan-2009 [18]. Note: unit of the left vertical axis is MWh, while unit of the right axis is \$/MWh.

As a consequence, investments in transmission and distribution facilities have mostly been falling since the 1990s [16]. Lack of investments limits network capacity, and thereby, imposing significant constraints on network power flows. Together with the rapid growth in electricity peak demand, this problem causes substantial stresses to the power system, sometimes to the point of cascading failures as occurred in the 2003 Northwest blackout in the United States [17]. Therefore, limited network investments during power system restructuring has contributed to the increasing frequency of blackouts.

### Market volatility

While power networks are suffering an increasing blackout frequency, electricity markets experience spot price volatility. As can be seen from the real market data in Fig. 1.3, spot price was stable around 35\$/MWh during most of the time, but jumped to over 10,000\$/MWh in some particular on-peak hours when the demands for electricity are extremely high. One of the main reasons for these price spikes is the exercise of market power by the Gencos. This problem can be explained by the following.

In the Australian National Electricity Market (NEM), Gencos make bids to supply certain amounts of power at corresponding preferred prices. The MO receives these bids, ranks them according to prices, and accepts enough bids to satisfy the forecasted demand plus a security margin. More importantly, the highest accepted bid price will be decided as the common spot price, which each Genco receives for the power they supply regardless of their own bidding prices. During the time of extremely high demand (such as those in

Fig. 1.3), Gencos may exercise bidding prices by raising them above the competitive level, if these players discover that these bids must be accepted by the MO in anyway to have enough power satisfying such a high demand. As a consequence of those strategies, spot price that is equal to the most expensive bidding price increases dramatically. Nevertheless, during some other periods with the same extreme level of demand (such as those in day 27-Jan-2009 and day 30-Jan-2009 in Fig. 1.3), somehow the Gencos cannot strategically exercise their bidding (the MO must have detected the source of market power, and thus, eliminating it by rejecting the strategic bids). Consequently, spot prices during these periods were low.

Spot price volatility caused by market power has been seen as the main reason for the recent California electricity market crisis [19]. During the period from May-2000 to September-2001, the city had a significant shortage of power supply due to a rapid growth in peak demand and the lack of investment of new generating plants. This shortage situation was unexpectedly exploited by some major Gencos—mainly Enron—who still had capacity available for power supply. In particular, Enron raised its bidding prices to a premium level, sometimes up to 20 times of the normal peak price, because it knew that such expensive bids must be accepted in anyway to compensate for the current shortage. This problem caused around 800% increase in wholesale spot prices from April 2000 to December 2000.

As a consequence, many Recos, who bought bulk electricity at spot prices and resell it to customers at regulated retail prices, lost significant money. Among those, Pacific Gas and Electric Company (PG& E) declared bankruptcy, while Southern California Edison (SCE) nearly ran out of business. According to the final report, this electricity market crisis costed around \$40 billion—most of which is incurred by the Recos [20].

The crisis is a very clear justification for the price manipulation problem in wholesale electricity markets. It also demonstrates a drawback of restructuring at the current stage. That is the still-strict regulation in retail markets, where prices paid by small customers are fixed as per retail contracts. Such prices do not follow the hourly variation of electricity spot prices, and consequently, do not reflect the “true cost” of power supply.

### **Peak demand**

Fig. 1.4 compares the growth in electricity peak demand and that of generating capacity in the United States during the period 1996–2000. As can be seen, the demand increased rapidly. Such a situation can be explained because personal incomes of residential customers were improved by 9.3% in California and 8.9% in the entire WSCC region. Such increased incomes resulted in more consumption of goods and services by the customers. As producing these goods and services is largely based on the utilization of electricity, an increased production entails increased demand for electricity.

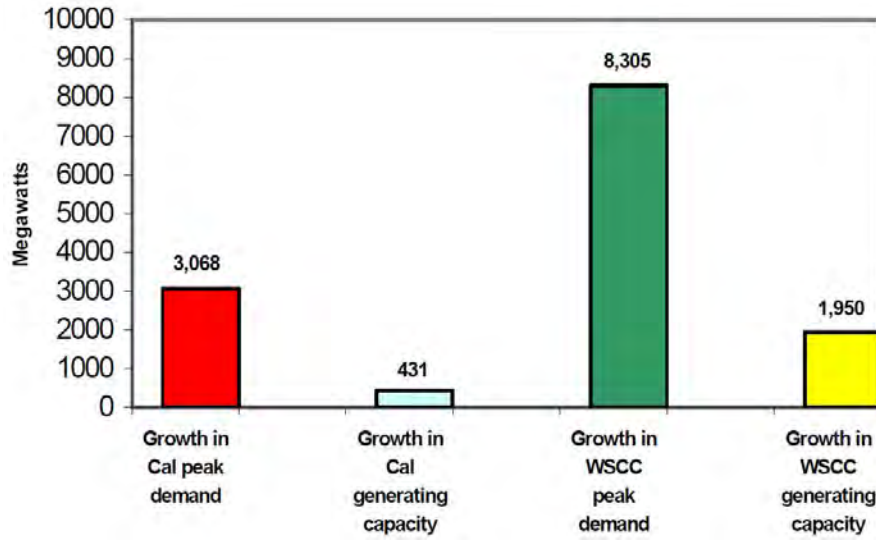


Figure 1.4: Comparison between the growth in peak demand and the growth in generation capacity during the period 1996-2000 within the California state and within the entire Western States Coordinating Council (WSCC) region [21].

Unfortunately, the rapid growth in electricity demand has been such a big problem for the supply side. According to market data shown in Fig. 1.4, investments of generating capacity were even below a quarter of the demand growth. Limited investments, as mentioned above, imposed significant constraints on the production and delivery of electricity. This problem has caused network blackouts and market crisis such as those happening in many large and industrialized countries during the beginning days of deregulation.

In summary, Section 1.2.2 presented some general problems associated network security and market volatility, as a direct consequence of power system deregulation. Next section introduces demand response (DR) as a potential solution to these problems.

## 1.3 Demand response

### 1.3.1 On the DR concept

Although electricity DR is not a new concept, its exact definition may be slightly different among nations, depending on their own economic contexts. In some countries where the power systems have still been under operation of a monopolized utility company, DR is often treated as an integrated planning resources to be used for the purposes of cost saving and energy efficiency over a long-term planning horizon (year-ahead) [22]. Such resources can be provided via fix-termed contracts being signed by both a utility and its customers. Determining the best contract options offering optimal benefits for both these parties, under regulation, is a complex problem that is however beyond the scope of this thesis.

In a competitive and deregulated environment, DR is defined as “*adjustments in electric usage by end-use customers from their normal consumption patterns in response to changes in electricity price over time, or to incentive payments designed to induce lower electricity uses at times of high spot market prices or when network reliability is jeopardized.*” [22].

This definition has been widely accepted as a benchmark for understanding and characterizing DR benefits under deregulation. From the definition, two key points are revealed. First, DR performed by customers can support both markets and networks in a restructured power system. Second, DR is not for “free”, meaning that player requesting a DR must compensate customer who provides it. Such a compensation could be either a change of electricity tariffs or an amount of reward unrelated to these tariffs.

Despite details provided by the above DR definition, there is one unclear point. That is, the definition does not specify how customers should be engaged in their DR activities. In particular, the phrase “changes in electric usage by end-use customers from their normal consumption pattern” does not indicate whether the customers must reduce, or just simply delay, their loads to perform a requested DR. While some customers can move their time-flexible loads (clothes washers) to another period just to reduce their consumption at the moment, other customers have to curtail loads (air conditioners) without being recovered, and thus, completely losing conveniences. Equal compensation to every customer will be consequently unfair to those who curtail loads. This problem is currently under debate [23]. It will be discussed further in the next chapter.

Should DR be understood as a resource supplied by customers or just another action taken by them in response to the market signals? This philosophical question also remains open at the moment. Some economists suggest that DR, by definition, refers to cases where the demand-side (customers) directly participates in a wholesale market in competition with the supply-side (Gencos). This means DR is viewed as an action of the demand-side. This action is certainly desirable, because it mitigates the consequence of market power exerted by the supply-side. During the California electricity market crisis, if the customers had responded to market price when it was extremely high, the Gencos (i.e., Enron) would not have such an opportunity to manipulate the market, causing substantial losses to the Recos [24].

Unfortunately, DR understood as market action does not reflect its benefits actually delivered to physical power networks. Such benefits are also desirable because they relieve network constraints during times of peak demand, and thus reduces the chance of component failures that may lead to a system blackout. No doubt, omitting the necessity of DR for network operations would lead to underestimating the actual DR benefits [25].

For this reason, this thesis views DR as a resource provided by customers to those players who use and pay for it. Such players include both market participants (Recos) and network companies (Transcos and Discos).

### 1.3.2 Estimating DR capacity and its financial benefit

In addition to the above definition of DR, here we give another concept—DR capacity—to help understanding the potential of DR as a market resource. DR capacity refers to “*the maximum portion of consumption, measured in percentage, which a customer can curtail (or shift) without losing its convenience in a given time period*”. Mathematically,

$$DRC^t = \frac{CC^t}{TC^t} \cdot 100\% \quad (1.1)$$

where  $DRC^t$ ,  $CC^t$ , and  $TC^t$  denote DR capacity, curtailable (or shiftable) consumption, and total consumption, respectively, during period  $t$ . Note that  $DRC^t$  given by (1.1) is individual capacity provided by one customer only. Aggregated capacity, which is supplied by a group of customers as a whole, can be calculated as the percentage of curtailable (or shiftable) consumption over the total amount, both are aggregated from all customers.

DR capacity has significant practical implications as it represents the ability of a customer to adjust its consumption for supplying DR. Since this measure is dimensionless, it allows a fair comparison between various customers having different living circumstances and thus different demands for electricity. Using this comparison, DR users (i.e., Recos, Transcos, Discos) can identify the best customers who flexibly perform DR without losing significant conveniences, and thereby, requiring *less* compensations than other customers. This competitive aspect will be discussed further in chapter 3 of this thesis.

DR capacity also helps regulators to understand the “true” potential of DR in their countries, and thereby, proposing appropriate market policies which promotes full utilization of such a resource. To demonstrate this potential, Table 1.2 gives a list of aggregated DR capacities for some large countries. These capacities are calculated using (1.1) with actual curtailable and total consumption data obtained from [26, 27, 30].

Table 1.2: DR capacities in some countries

Country	Maximum capacity	Current utilization
U.S.A [26]	35%	5%
Australia [27]	50%	3%–5%
U.K. [30]	40%	2%

As can be seen, the current DR capacity utilizations are far less than the corresponding maximum capacities in those countries. The utilization in U.K. (around 2%) is even lower than those in U.S. and Australia (5% and 3%–5%). These statistics can be explained by several economic and technical reasons, including high compensations required by customers for supplying their DR, lack of coordination in scheduling DR across all customers, and also lack of innovative technologies to be used for controlling customer appliances.

These statistics also suggest that there are potential areas for improving DR capacity utilization. This improvement is highly desirable, because it would bring out significant additional market benefits. To illustrate such benefits, Table 1.3 shows a simple and yet realistic financial valuation of the DR capacity in Australia. Results are extracted from an empirical study conducted by the Energy User Association of Australia (EUAA) during the horizon 2003-2005 [27].

Table 1.3: Annual estimate of financial DR benefits in NEM

Scenarios	Gross benefit(\$)	Compensation(\$)	Net benefit	
			(\$)	(% of TMR)
Current utilization (<5%)	76 mil	15.2 mil	60.8 mil	0.5%
Improved utilization (5%–15%)	420 mil	60 mil	360 mil	3.1%
Full utilization (50%)	2 bil	270 mil	1.73 bil	14.4%

As can be seen, the current market scenario with lowest capacity utilization offers very little compensations for DR-providing customers. The collective net benefit to the market (as a whole) is \$60.8 millions that accounts for only 0.5% of Total Market Revenue (TMR) (currently around 12 billions). If the DR capacity is fully utilized (i.e., up to 50%), substantial benefits will be obtained including \$270 millions for all customers and \$1.73 billion (14.4% of TMR) for the whole market. These estimates demonstrate the potential of DR in Australia, motivating the capacity utilization improvement.

### 1.3.3 Major challenges in scheduling DR

The utilization of DR capacity can be significantly improved by introducing an appropriate scheme for scheduling DR. This essential idea, which was originally proposed by Schweppe [29], has become a topic of interest to the power engineering community in the last twenty years. In general, DR scheduling aims at determining optimally which customers should adjust consumption and to what degree they need to do so.

Scheduling DR for a local group of customers may not be difficult, but the scheduling for all customers across the whole power system is a challenging task. It entails considering not only the compensation for customers adjusting their consumption but also the benefits for any stakeholder involved in a deregulated power supply system. Such players generally include Transcos and Discos who claim network reliability benefits, as well as the Recos who gain the benefit of mitigating spot price volatility in a wholesale electricity market. All these benefits are derived from a common DR capacity in the form of load reduction during peak demand.

Another issue of DR scheduling relates to load recovery—the process by which electricity customers restore their consumption following load reduction [23]. This process can

have a significant impact on power system operations as it increases the cost of electricity supply during recovery hours when the Recos have to buy additional electricity from a volatile wholesale spot market and the network operators (i.e., Transcos and Discos) must deliver additional power using their already-constrained networks. Lack of the recovery effect consideration in DR scheduling may lead to underestimating the electricity cost and then overestimating the DR benefit along the scheduling horizon [23].

From the above discussion, one can see that scheduling the DR entails considering two fundamental elements—space and time. The former refers to a number of business sectors (i.e., transmission, distribution, and retail) at different locations in a power system. As these sectors are operated independently by a range of players (Transcos, Discos, Recos) via deregulation, scheduling DR over the space requires assessing benefit for each of them. The time-based criteria, on the other hand, entail profit optimization across a given time horizon (i.e., a day, a week, a month), considering the intertemporal effects of load recovery on the electricity supply chain.

## 1.4 Overview of the research

With reference to the above general criteria, this thesis presents a new development towards a comprehensive solution for scheduling DR. This development involves both market design and evaluation stages. In the former several new concepts and mechanisms are proposed as a basis for scheduling the DR in a systematic manner. These proposals are then evaluated in terms of economic efficiency, using standard cost-benefit analysis methods. To our knowledge, no published work offers a similar development with this thesis. In fact, the contribution here should be regarded as “interestingly unusual” to the extent that it is almost independent of any DR research published over the last five years.

For clarity, our DR scheduling work is divided into three closely-related topics to be presented in different chapters of the thesis.

### 1.4.1 The concept of demand response exchange

The first and most important concept proposed in this thesis is Demand Response eXchange (DRX), in which DR is treated as a market product to be negotiated between two groups of participants—buyers and sellers. Buyers (i.e., Transcos, Discos, and Recos) need DR for their risk management benefits (i.e., associated with network reliability and market volatility), while sellers (i.e., ESCos in behalf of electricity customers) have the capacity to significantly modify electricity demand on request of the buyers. The concept of DRX represents a new and separate market for trading DR in a liberalised power system. Indeed, it reflects a novel view into the problem of efficient DR scheduling from an economic perspective.



The DRX concept is explored as a result of substantial literature review in **Chapter 2**. Most existing works in the research area of DR scheduling can be classified into three broad categories based in which player is central to the development. These are Transco-based, Reco-based, and Disco-based. These categories unfortunately represent only partial scheduling approaches as they consider DR benefits for only a subset of market players, either Transcos, Discos or Recos. This limitation indicates lack of scheduling coordination across the players, and this could be seen as the main reason for inefficient DR scheduling followed by low capacity utilizations, as has been demonstrated by the real data given in Table 1.2. This problem essentially motivates the development of a DRX, which is viewed as a comprehensive DR scheduling scheme considering benefits across all players.

### 1.4.2 Market clearing mechanisms

As with all other open markets, DRX requires a market clearing mechanism<sup>1</sup>. By “market clearing”, we mean that DR is to be scheduled in terms of a set of quantities (in MWh) and prices (in \$/MWh), with the major aim of optimizing overall market efficiency across all DR buyers and sellers. There are two market clearing mechanisms to be proposed in this thesis, namely pool-based and agent-based. They represent different paradigms (i.e., centralized versus decentralized) in operating an open market. We should emphasize that these DRX schemes are considered to be independent of the existing wholesale and retail electricity markets, as will be discussed throughout this thesis.

In a pool-based DRX market developed in **Chapter 3**, DR sellers (ESCos) and buyers (Transcos, Discos, and Recos) are required to submit offers and bids reflecting their own marginal costs and benefits derived from DR. Using this collected information, the market operator centrally maximizes the total market benefit under economic constraints such as the demand–supply balance, and the contribution of each buyer for DR as a public good. Such a pool-based clearing scheme, following a standard market design, is a formalization of the concept DRX.

Under an agent-based market clearing scheme developed in **Chapter 4**, each participant (DR buyers and sellers) is treated as an economic agent behaving in a self-interested manner. This means the agents only attempt to maximize their own benefits based on the available information about actions taken by other agents participating in the same market. The scheme will be designed according to this assumption. The main design objective is to constrain each self-interested agent to ensure optimal global market efficiency, while also enabling agents to maximize their own (local) benefits. The key ingredient of such a decentralized operating paradigm is the notion of competitive market equilibrium at the point where 1) all market agents (DR buyers and sellers) maximize their benefits simulta-

---

<sup>1</sup>Throughout this thesis, the two terms “mechanism” and “scheme” are used interchangeably

neously subject to the given prices; and 2) there is a balance between supply and demand for DR product. Both the existence and uniqueness of this market equilibrium in a DRX market are proven to satisfy under a few justifiable assumptions (i.e., preference convexity) that is commonly used in economic analysis.

In general, it is hard to compare the pool-based and the agent-based schemes, each has their own advantages. The major strength of the former lies in its centralized optimization, in which all DR resources are aggregated and valued simultaneously, in the effort of making a fair resource allocation across all market players. The agent-based clearing mechanism with local optimization, on the other hand, is flexible as it can deal with a range of varying system conditions.

### 1.4.3 Cost-benefit assessment framework

Although DR scheduled via DRX schemes can improve network reliability and mitigate electricity market volatility in a deregulated power supply system, estimating its financial value actually delivered to the system is not simple. This entails assessing all relevant costs and benefits derived from the DR. Without a rigorous assessment tool, justification of the system improvements using DR is almost impossible [22]. Over the years, there has been substantial research on this DR cost-benefit analysis<sup>2</sup> topic. Most of this research focuses on only a few actors in a deregulated power system [28]. For example, some works analyse the benefits for customers, Recos and Gencos in isolation to the Transco and Discos, while other works consider the Discos and the Transco only.

Unfortunately very little attention has been paid to developing a comprehensive framework for assessing DR costs and benefits across all players. This framework, considering a global viewpoint, is important because without it, DR may never be fully evaluated and thus cannot reach its potential. For example, a plan to optimize DR benefit for one player could result in a conflict with another when both players rely on DR capacity supplied by the same set of consumers. Due to this conflicted plan, the total market benefit could be significantly diminished or even negative, eliminating the overall efficiency of DR. Thus, a realistic DR framework will allow us to analyse the plan of one player in relation to other players, and then to optimize the total benefit for all of them.

With reference to the above literature review, in **Chapter 5** we develop a comprehensive framework for assessing financial costs and benefits of DR for all actors in an electricity supply chain. We then use this framework to study the relative economic efficiencies of various DR scheduling schemes including the proposed DRX and the existing partial schemes. This study, which is based on a rigorous analysis with justifiable assumptions and realistic data, will substantiate the advantages of our DRX proposal.

---

<sup>2</sup>Throughout this thesis, the terms “assessment”, “evaluation”, and “analysis” are used interchangeably

In addition to being able to assess various DR scheduling schemes, the proposed framework is necessary to analyse the potential effects of DR-related regulations, risk management, or other strategic interventions. In this case, the framework becomes a useful off-line tool for comparing various market designs, by assessing their relative impact on network utility, and thereby guiding selection of the best option for future power system management.

## Chapter 2

# Literature Review and Demand Response eXchange

### 2.1 Overview

This chapter discusses the necessity and feasibility of demand response exchange (DRX) as a new and separate market for trading DR in restructured power systems. The former arises due to the fact that most existing works in this area constitute only partial solutions for scheduling DR, and therefore they are not efficient from a global point of view. In this regard, one should develop a comprehensive approach following the general DR scheduling requirements.

The feasibility of DRX relies on power system restructuring. As the power environment has been deregulated, the vertical utility company is broken into a number of independent players including Gencos, Transco, Discos, and Recos. Since most of them are interested in purchasing DR as a market product from electricity customers, they can be considered DR buyers and the customers DR sellers. Introducing competition between these buyers and sellers is a promising way of achieving efficient DR schedules. Such a competition can be motivated by setting up a unified market, DRX, where all players gather to exchange their DR products.

The chapter is structured as follows. Section 2.2 reviews the existing approaches for scheduling DR. Section 2.3 introduces the proposed DRX approach and explains its feasibility via deregulation. Section 2.4 discusses practical implications of DRX, i.e., how it interacts with other markets within the restructured power system. The implementation of DRX as part of smart grid development campaign is briefly mentioned. Concluding remarks are finally given in Section 2.6.

## 2.2 Existing approaches to DR

Although the benefits of DR are well-understood, developing a comprehensive DR scheduling program capturing all these benefits together is not a simple task—it entails substantial research. This section reviews published works in this area.

To handle a very large amount of literature on scheduling DR, classifying it into different categories is necessary. Traditionally, DR research has been categorized as “pricing” or “rewarding” based on which financial incentives are offered to customers for their DR [22]. This classification approach, however, may be ineffective because it does not reflect the DR benefits for each individual player. That is, which independent players among Transcos, Recos, and Discos are managing DR and how much benefits they individually gain from it. This aspect is important because it would represent the interactions between different players regarding how the common DR is scheduled and compensated under deregulation. Following this aspect, here we alternatively classify the literature into three broad categories, based on which independent players are central to the analysis [25], as given in Table 2.1.

Table 2.1: Summary of existing DR research

Classes	Participants	Types of DR	Particular research topics
Reco-based	Recos	Pricing	Risk hedging
	Customers	Rewarding	Demand-side bidding
Transco-based	Transcos	Rewarding	Demand-side reserves
	Customers		Negative generation
Disco-based	Discos	Rewarding	Feeder’s load scheduling
	Customers		Distributed resources

### 2.2.1 Reco-based scheduling

This research category relates to cases where DR performed by a group of customers is scheduled and paid by the corresponding Reco having pre-contracts for retailing electricity at given prices to those customers. Typical examples of Reco-based scheduling could be found in [33–47].

A Reco often benefits from DR by using it to cover risks caused by spot price volatility in the wholesale spot markets. In economic theory, such a strategy is referred to as a financial hedge, in which the Recos offset investment (i.e., the demand to be met from spot markets) in order to minimize unwanted exposure to volatility risks. This is done by using DR to reduce the amount of power the Recos need to buy during periods of high spot prices. In this strategy, the gross benefit derived from DR is equivalent to the benefit from risk reduction that can be calculated using a hedge analysis.

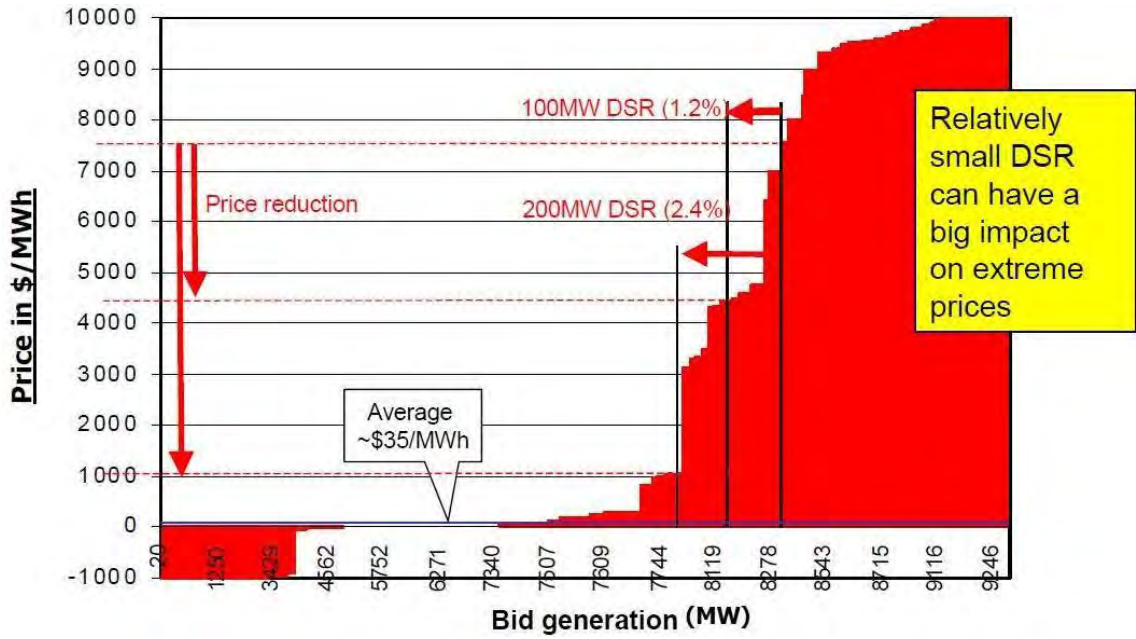


Figure 2.1: A sample of hourly generation bidding prices in NEM, showing the potential impact of relative small demand reduction on spot price [27]

The above DR benefit for Recos is illustrated using actual market data shown in Fig. 2.1. In this example, reducing 1.2% of total electricity demand would have reduced the spot price from \$7,500/MWh to \$4,500/MWh. Similarly curtailing 2.4% of the total demand would have brought the price down to \$1000/MWh. Supposed that retail price to every customer, as per retail contract with the corresponding Recos, is fixed at \$200/MWh, those dispatched DRs (1.2% and 2.4%) would save around \$25 million and \$54 million, respectively, for all Recos buying bulk electricity at extremely high and volatile spot prices and reselling this amount to customers at low and fixed retail prices. This business case facilitates understanding DR financial benefits given to the Recos.

To motivate customers performing DR for supporting risk hedging, either price-based time-varying tariffs or reward-based options can be offered by Recos. The design of time-varying tariffs is largely influenced by pioneering works of electricity spot pricing generally [33] and peak-demand pricing in particular [34]. The concept of spot pricing was expanded in [35] by incorporating it with the estimation of day-ahead marginal cost of serving given peak demand. A hierarchical framework was developed in [36] to maximize Reco benefits while controlling marginal-cost-based tariffs. Additionally a theory of inverse pricing based on the fact that energy consumption is inversely proportional to price has been applied in [37].

On the other hand, designing appropriate rates for reward-based DR options, such as direct load control, can be performed using statistical survey in the form of questionnaire [38] or quantifying interruption costs to market participants [39]. Since this cost cannot

be estimated accurately, determining how much reward offered to the customer for its demand reduction is not simple. In [40], the authors used game theory to design optimal load curtailment programs without requiring knowledge of customer outage costs. In [41], the authors developed a load valuation model for both Recos and their customers to select optimal rewards for interruptible loads.

In addition to risk hedging using DR, Recos may consider demand bidding into the wholesale markets, in competition with the supply-side (Gencos) [42–45]. In this strategy, each Reco submits a price-responsive bid to the market operator, specifying how much electricity to purchase at different spot price levels in a given hour or a given day. Demand bidding has been proposed as an effective way of mitigating market power exercised by Gencos in pool-based electricity markets [46], but it has not been widely implemented [47]. Note also that DR and demand bidding are different activities. The former is performed by a customer to augment the latter for the contractual Reco.

### **2.2.2 Transco-based scheduling**

This category refers to present whenever DR from customers is managed by a single Tranco operating an interconnected transmission network where bulk electricity is delivered from large generators to customers at different substations. Examples of Transco-based DR scheduling are given in [48–55].

These stakeholder utilize DR for managing security of their transmission networks. Traditionally, the network security is maintained through preventive measures—the network is prepared in advance to withstand credible outages with no need for any immediate corrective actions, such as involuntary load shedding, generation redispatch, to be taken following an outage. The advantage of such an operating philosophy is simplicity of security management. Unfortunately it has an important drawback that it increases operating costs and lowers network capacity utilization [31]. In this regard, an additional operational requirement would be to operate the transmission network at a lower cost and higher network utilization. This requirement can be met by using DR in the form of load reductions at appropriate network locations.

Fig. 2.2 illustrates using DR for managing network security and enhancing network utilization within a given capacity limit. In this example, the network maximum capacity is around 10 MW that is far above the actual loading level during most of the day, except for some hours in the early morning and then in the early evening. To maintain the security during these on-peak hours, either network capacity need to be upgraded via infrastructure investments, or some loads must be curtailed. Although a higher capacity can better withstand contingencies during peak demand, its utilization in off-peak hours drops significantly because a low network loading level during these hours would not require such a high capacity (See Fig. 2.2). Consequently, using DR in the form of load reduction

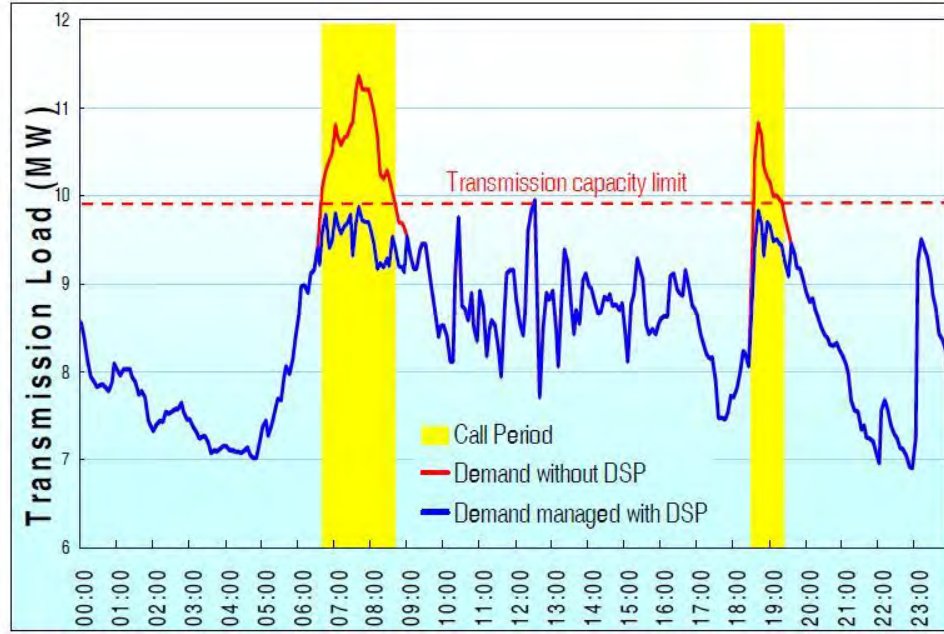


Figure 2.2: Using DR to reduce electricity demand following transmission capacity limit

is preferable, in the sense that it improves the overall network utilization, and thereby, reducing the need for new investments while still maintaining the network security. These DR benefits are given to Transcos and will be financially quantified in Chapter 5.

Transco-based DR scheduling research often focuses on two main topics, demand-side reserves and negative generation. Using DR as demand-side reserve supporting transmission network reliability has long been of interest to the power engineering community. Improved network reliability results from reducing the probability of forced outages when system reserves provided by the supply-side (i.e., synchronized generators) fall below a desired level. By reducing electricity demand at critical times when a generator or a transmission line is unexpectedly lost, DR as demand-side reserve scheduled by the Transco can help to return the overall system reserve to the pre-contingency level, and thereby, enhancing the network reliability [22]. In [48] the authors suggested that both demand- and supply-side reserves can be procured through a separate market that is secondary to the energy spot market. In the former, a Transco on behalf of its network users buys reserves from sellers such as Gencos and customers. Using this context, a stochastic model for the Transco to calculate the optimal reserve level considering both credibility and severity of network contingencies, as well as payments to the sellers, was proposed in [49].

DR as demand-side reserve can also be purchased through a joint energy/reserve market [50–54]. In this context, electrical energy and system reserve aggregated from both demand and supply sides are scheduled simultaneously, with the aim of optimizing the total benefit of using all these resources. As was proposed in [50], consumers can participate



in the market by submitting offers to provide up-spinning and standing reserves. Using the same idea, a market model, where reserve providers are paid an option fee to compensate for their opportunity cost and an exercise fee if they are actually called during a contingency event, was presented in [51]. This work introduces the cost of exercising reserve option as an important factor in the co-optimization problem.

In the above works on joint energy/reserve scheduling, DR in the form of load reduction was implicitly considered “negative generation” competing with the actual generation resources in the same wholesale market [52]. Such an operating philosophy is currently under debate. In [53], the authors argued that the competition between negative and actual generators would be “artificially” inflated, in the sense that it causes price spikes if the effect of load recovery in off-peak hours following load reduction during peak-demand is not taken into account in the scheduling optimization problem. Following this argument, some researchers have incorporated the load recovery effect as an important parameter in scheduling DR. In [54], the authors presented a study on controlling aggregated load of a group of small customers, with the purpose of participating in an energy balancing market. Here the marginal value of DR is calculated considering both benefit of load reduction and cost of serving subsequent load recovery.

### **2.2.3 Disco-based scheduling**

This class of DR research represents situations where DR made by customers is scheduled by the corresponding Disco operating a local distribution network consisted of many radial feeders where end-use customers are directly connected with. Examples of Disco-based scheduling are provided in [55–62].

As with Transcos, Discos use DR to manage network constraints at distribution level. In general, DR brings out an array of potential benefits that can even be more diverse than those at the transmission level. These benefits include: 1) deferring new network investments; 2) relieving voltage-constrained power transfer problems; 3) simplifying outage management; and 4) enhancing the quality of power supply to end-use consumers [32].

There is a particular emerging issue associated with the increased loading of existing distribution substations in urban areas, driven by significant increases in air-conditioning loads [32]. DR therefore can be utilized to manage such increases, and thereby, enhancing the loading capability of existing substation transformers. These network reliability benefits derived from DR are all given to the corresponding Discos and will be financially quantified in Chapter 5.

Disco-based DR scheduling research often focuses on two main topics, feeder’s load scheduling and distributed resources. Research into suitable algorithms for load scheduling within a local distribution feeder has long been of interest. In [55], a relaxed dynamic

programming was used to generate daily optimal control strategies for a group of residential air-conditioning loads. In the same context, [56] and [57] considered a multiple objective evolutionary approach utilizing genetic algorithm (GA) for designing and selecting optimal load control actions. A least enthalpy estimation (LEE) method was developed in [58] to minimize the amount of load interruption under several customer-driven constraints such as outdoor temperature, thermal comfort level and payback load effect. A binary particle swarm optimization (BPSO) was proposed in [59] to schedule a significant number of interruptible loads with the aim of meeting a given system requirement for the total hourly and daily load curtailments while ensuring enough compensation for the curtailing customers. A game theory approach is provided in [60] for autonomous demand management where several neighbouring households share a common energy source.

Distributed energy resources (DER) recently receive much attention from researchers. Although DER includes both small-scale power generation and demand management by individual customers, the former is not explicitly addressed in this thesis. DER supports a local electric system (i.e., microgrids) by alleviating the need for using centralized generation plants whose power must be delivered to customers over long-distance transmission lines. In [61] a multi-agent approach is developed to schedule DER within a medium-scale microgrid comprising up to 500 loads, each treated as an agent. Here non-market algorithms such as GA for agent local optimization were investigated. In [62], the authors proposed a decision-support tool for residential customers to manage their acquisition of energy services, by enabling these customers to assign values to desired services and then to schedule their available DER, with the aim of maximizing their service benefits. To schedule DER, here BPSO algorithm was used because of its demonstrated ability to obtain optimal DER schedules within a reasonable computational time.

#### **2.2.4 Common limitations**

All three DR categories (Reco-based, Transco-based and Disco-based) constitutes only partial solutions to the general requirement of an effective DR scheduling program, because they focus on optimizing DR benefits for only a subset of stakeholders in a restructured power system (see Fig. 2.3). For example, the Reco-based approach described above focus on benefits for Recos acting independently who may, as a consequence of their unilateral DR activities, have an adverse impact on Transcos or Discos. It is important to understand that all players rely on DR capacity provided by the same set of customers located within a single geographical area. In light of the shared underlying resource, any partial DR scheduling approach could be significantly sub-optimal technically, financially and socially [25, 63, 64].

From a technical point of view, optimizing DR benefits for individual players can result in conflicts over how the same DR capacity (i.e., customer load) is scheduled. For example,

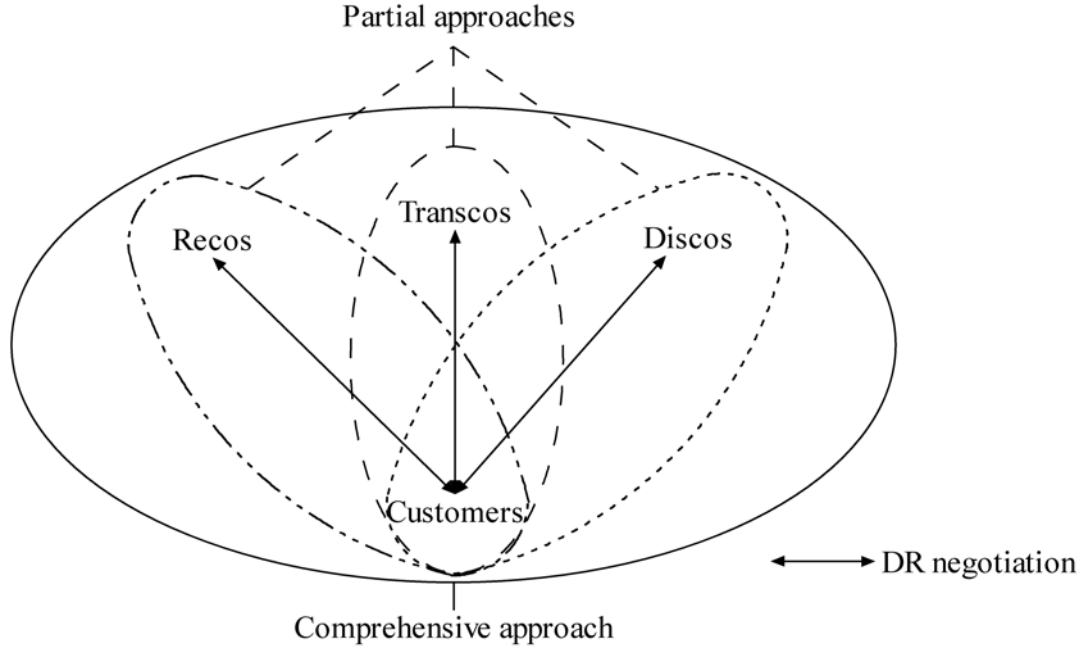


Figure 2.3: Circling different types of DR scheduling approaches

a Disco can produce a plan specifying optimal DR scheduling to fix reliability problems in the distribution network while, at the same time, the Transco might produce another plan to address a contingency within the transmission network. Since these two contingencies appear to be independent events within different networks, the plans produced by the Disco and the Transco would be developed separately [65]. Should there be some overlap in the scheduled DR capacity serious grid management problems can arise.

Additional resource scheduling conflicts arise from Recos using DR to mitigate the impact of spot market price volatility. Such volatility originates from Gencos responding to supply shortages and the increased cost of running peaking power plants [66]. Consequently, generation costs are decoupled from those of network contingency management, which results in another source of DR scheduling conflict. In this instance, an optimal DR plan produced by a Reco to deal with the spot price volatility could conflict with a plan produced by the Transco and Discos to deal with network contingencies.

From the economic perspective, any partial approach is inefficient. Since DR benefits for each player are determined unilaterally, it is difficult to calculate the social benefit (i.e., the sum of benefits for all individual players). The social benefit is probably more important than individual benefits since it indicates the usefulness of DR for all stakeholders. Due to conflicts between individual benefits, the social benefit of DR can be significantly reduced or even become negative.

Finally, any partial approach results in lower returns for customers who provide DR capacity, because this approach assumes that customers are rewarded by a single player

requesting DR. In reality, customers should be able to offer their capacity to all players, and thereby increasing the value of that capacity. Limiting the range of DR-involved players reduces the reward to customers, and thus reducing the supply of DR capacity, as has already been seen in both U.S. and Australia energy markets (see again Table 1.3).

### **2.2.5 Comprehensive DR scheduling requirements**

Because of the above issues with partial DR schemes, there is a great interest in finding a comprehensive approach to DR scheduling considering benefits across all players including Recos, Transcos, and Discos (see again Fig. 2.3). This approach would be both more reliable and efficient than any partial approach, since it aims to optimize the overall DR benefit for all players while solving the scheduling conflicts between them. Similarly, it would reward the customers better by allowing them to deal with multiple DR-involved players.

It is important to understand that developing a new comprehensive approach would not necessarily contradict with the existing partial schemes. Rather it should be viewed as a “framework” incorporating advantages of these schemes and overcoming their limitations. The main advantage is that each independent player under deregulation has considered using certain “self-motivated” techniques for utilizing DR more efficiently. For example, the Recos have augmented self-imposed risk hedging and self-imposed demand bidding using DR, to compete well with the Gencos in wholesale electricity markets. On the other hand, the main limitation of partial schemes is, as discussed above, lack of coordination across all independent players regarding how the common DR provided by customers is optimally scheduled.

To overcome the coordination problem while inheriting the self-motivated advantage from existing partial schemes, this thesis introduces a novel comprehensive DR scheduling concept—Demand Response eXchange (DRX)—which is a well-organized and competitive market for trading DR across all involved players.

## **2.3 Proposed DRX approach**

### **2.3.1 Scope of the proposal**

Until now, our discussion has focused intensively on DR benefits for the supply-side (i.e., Recos, Transcos, Discos). Here we consider some important aspects from a demand-side perspective. They also clarify the scope of our proposal.

#### **Pricing vs rewarding**

Which incentive should be given to customers for providing DR? As discussed above, it can be either a price or a reward. Under dynamic retail pricing, customers reduce their

consumption in response to high price during on-peak hours, and then, recovering this consumption when the price goes down (i.e., at nights). By doing so, the customers could reduce their electricity payments while not losing their conveniences [65]. However, there are some practical concerns about dynamic pricing.

First, if all customers pay the same rate (i.e., uniform price), those who adjust consumption will be disadvantaged comparing with those customers doing nothing but at the same time enjoying the common pricing benefit. Such a ‘free-riding’ issue has long been discussed by economists in the context of electricity markets [42].

Second, if each customer pays an individual price depending on their own consumption, it would again be unfair to those customers having special living circumstances. As pointed out in [37], individualized pricing works according to the fact that electricity price is inversely proportional to demand. That is, customers with high demand elasticity face only a small price ‘markup’ by the retailer. By contrast, inelastic customers (for instance, the disabled or old) who are unable to adjust their demand suffer a relatively high markup. Politically, such customers should also be viewed as those for whom electricity consumption is vital [37]. Then charging them a higher price markup than others will be challenged as unfair. This situation is commonly known in economics as the ‘Ramsey’ problem that eventually distorts the overall efficiency of dynamic pricing. Such a distortion can be justified empirically, for instance, by consumer advocacy groups (e.g. [67]).

For these two reasons, this thesis employs reward as an alternative type of financial incentives given to customers by an array of players (Transcos, Discos and Recos) who benefit from DR capacity provided by them. Such rewards are considered to be unrelated to the retail prices that are offered by the Recos only.

### **Load shifting vs load curtailment**

How customers should be engaged in their DR activities? This engagement can be either load curtailment or load shifting. Intuitively, the latter is more suitable to customers, because if they reduce their consumption during on-peak periods without catching up at other times, the value they put on electricity is not consistent [23]. This simply implies that customers always prefer shifting some of their loads to a future time in response to incentives offered at the current hour. While load shifting is beneficial to the demand-side, it causes several problems to the supply-side (i.e., Recos, Transcos, Discos).

If all customers together reduce and then recover their loads, the resultant total demand during a catch-up period would become just another peak. Serving this peak demand, again, requires a considerable effort of the supply-side [34]. The network operators have to pay more attention to system security due to heavy constraints imposed on the networks under high loading conditions. What is worse, the wholesale market may in that catch-up period experience sharp and unwarranted increase in electricity spot prices. As explained

in [53], this problem is due to the lack of load recovery consideration within the market scheduling. Lack of attention by the market operator will be vulnerable to price manipulations by some large Gencos, who still has capacity available for serving the unforeseen demand recovered by customers.

Despite its important impact, load recovery complicates the calculation of DR benefits across the entire scheduling horizon. As was suggested in [54], the marginal value of DR should be calculated by taking into account both benefit of load reduction and cost associated with load recovery. While the former relates to only one period when a DR is requested, the latter would occur whenever customers restore their consumption. From the supply-side perspective, identifying the exact recovery periods which are solely, and maybe arbitrarily, decided by the customers is not an easy task.

No doubt, to make load shifting work, all above recovery issues must be addressed properly. These issues are, however, beyond the scope of this thesis. Rather this research considers the case of load reduction requested during the current period only. In this sense customers may, or may not, recover consumption in a future time. If they do, they would require just a little compensation due to some minor inconveniences caused by temporary consumption delay at the moment. Otherwise, much higher incentives have to be provided for the without-recovery load curtailments (i.e., air conditioners, refrigerators). As will be shown, such incentives will be rigorously determined by the proposed DR market.

### Energy Service Companies (ESCOs)

What is the particular role of an ESCo in scheduling DR? In many real markets in Australia and the U.S, ESCOs have developed dedicated systems for their customers to register, aggregate, schedule, dispatch and settle the DRs requested by those players on the supply-side [68]. Examples of ESCOs engaged in DR business, are given in Table 2-7 [72].

Table 2.2: Some large ESCOs

Company	Country	Day-ahead	Day-of	Curtailment window
Energy Response	Australia	No	Yes	7 a.m.—10 p.m.
EnerNOC	U.S.A	No	Yes	11 a.m.—7 p.m.
Energy Connect	U.S.A	Yes	No	10 a.m.—5 p.m.
CPower	U.S.A	Yes	Yes	11 a.m.—7 p.m.
NA Power Partners	U.S.A	Yes	Yes	10 a.m.—6 p.m.

Note that all ESCOs listed in Table 2.2 offer reward-based load curtailments during each agreed period termed ‘window’. Until now, they have not considered 1) using price to motivate their customers providing DR and 2) analyzing effect of any possible load recovery following a load reduction.

It is also important to clarify that the functionalities of an ESCo are different from those of a Reco, although they both deal with customers [68]. In fact, ESCos never buy bulk electricity from wholesale markets at spot prices and resell the electricity to small customers at retail prices. In this regard, ESCos have no control over such prices. This is desirable because if an ESCo has the right of adjusting retail prices paid by its customers, it may, as similar to some existing strategic Gencos and Recos, manipulate such prices for its own benefit. The objective of an ESCo should be to help the customers in their demand management, not to control or command them.

This thesis, for practicality, considers ESCos who, on behalf of their customers, negotiate DR with all players on the supply-side.

### 2.3.2 On the DRX concept

Considering the case of ESCo-supported reward-based DR either in the form of load curtailment or load shifting, this thesis proposes a novel scheduling concept—Demand Response eXchange (DRX)—“*where DR is treated as market resource to be exchanged between buyers and sellers. Buyers (Transcos, Discos and Recos) need DR to improve the reliability of their electricity dependent businesses and systems. Sellers (ESCos) have the capacity to significantly modify electricity demand on request.*”

The proposed DRX concept is illustrated by Fig. 2.4. Here the core idea is to consider DR a market product (or resource) that can be supplied by ESCos and is demanded by Transcos, Discos, Recos. The supply of DR is a “virtual” procedure by which customers reduce their consumptions during peak demand, as is requested by those on the demand-side of a DRX. The negotiation between supply-side and demand-side is performed via the so-called market transactions that determine both optimal quantity and price of a DR being scheduled. Multiplying DR price by quantity gives a payment to be made by the buyers (Transcos, Discos, Recos) for the sellers (ESCos) who supply DR.

In a DRX, each market participant has a specific role according to their pre-existing functionalities. In addition to the DR buyers and sellers who are the main actors in the market, there are DR producers (i.e., electricity customers). They generate DR resources by curtailing loads during peak demand following the outcome of DRX market negotiations, and then are compensated by the corresponding ESCos using DR payment collected from the buyers. Such an arrangement between customers and their ESCos is somewhat similar to those in an electricity wholesale market where generating units produce electricity to be sold by the corresponding Gencos.

The most important advantage of a DRX over conventional partial approaches described in Section 2.2 is that all players (Transcos, Discos, Recos, ESCos, and customers) are “integrated” into a common framework for scheduling management and analysis. More

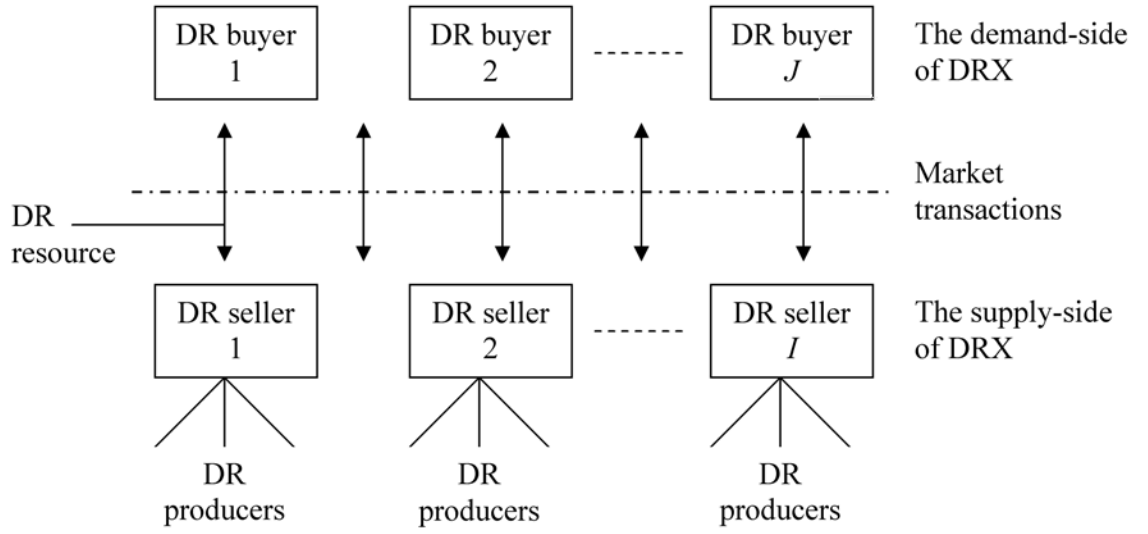


Figure 2.4: Demand Response eXchange

specifically, this framework considers multiple DR buyers who may together use common DR resources supplied by the same set of customers via their ESCOs. By contrast a conventional partial approach (i.e., Reco-based) focuses on the analysis of only one buyer and omit others.

In the DRX framework, both competition and coordination in scheduling DR across all market participants is introduced as a mean of achieving global market efficiency.

**Competition** implicates that if any seller requires a payment far above the true cost of producing DR, it may lose the selling opportunity to other players who require less payment. Similarly, if any buyer prefers a DR price much lower than actual benefit, it could not purchase this DR that is better owned by other buyers who can afford a higher price. In order words, competition can improve price-based allocation of the underlining resource (DR) across all market participants.

In addition, competition motivates sellers to develop new technologies for producing DR more efficiently, reducing cost, and thus, enhancing the competitiveness of the product. Buyers, on the other hand, has to consider using innovative methods for utilizing DR better, in the sense that the benefit derived from the DR is improved. As such, the buyers are willing to pay a higher price, consequently becoming more competitive in purchasing DR.

**Coordination** refers to cases where all DR resources are evaluated and scheduled together for a common goal of optimizing total benefit for all market participants, who either produce or use these resources. The optimization process is supervised by the DRXO who may, or may not, intervene directly in the negotiation between sellers and buyers.



Coordination helps solve possible conflicts among individual players who have “personal” interests in scheduling DR. As will be illustrated in Chapter 6, without a scheduling coordination across all players, the total DR benefit for them may become significantly suboptimal, sometimes to a negative value due to unsolved personal conflicts.

### 2.3.3 DRX models

The above conceptual discussion has raised the need for developing a market model for DRX. This model not only formalizes the exact description of what DRX will do, but also specifies which infrastructure is required for DRX operations. It is necessary that either such infrastructure has already been implemented, or the technologies required to implement the infrastructure are well-developed and ready-to-use [68]. This implementation issue will be discussed later in this chapter.

This research introduces two fundamental market models for DRX, namely bilateral and pool-based, as shown by Fig. 2.5. In the former, seller and buyers independently arrange DR exchange, setting by themselves the amount of DR and its payment without third-party interventions, for instance, by the DRXO. Nevertheless, this regulatory body should still supervise the DRX market by determining whether participants obey given market policies. The pool-based model, on the other hand, refers to central market coordination and settlement by the DRXO. The term “pool” implicates that all DR capacity is aggregated into a virtual pool managed by the DRXO, and all sellers have to access this pool to purchase needed DR.

These two market models represent different levels of *competition* and *coordination* among participants. The bilateral model generally promotes “free” market competition by allowing independent negotiation between every two parties (a buyer and a seller). In this situation players become highly motivated to strengthen their production and utilization of DR resource. The “weak” player may be easily dominated by the stronger, and this would improve the overall market performance. However, free competition could be vulnerable to market manipulations by those dominant players, in the sense that they attempt to exercise market power by creating artificial, false or misleading appearances of the market price. A similar case had been experienced by California electricity market during the 2001 crisis, where some large Gencos (i.e., Euron) raised the spot price up to 800% of the normal peak value. To mitigate such manipulation problems in a DRX market, coordination is required which can be offered by the pool-based model.

Under a pool-based operating paradigm, sellers and buyers also seek profits while the DRXO ensures that no market manipulation can occur. By examining all data aggregated from participants, the DRXO could detect the source, and to analyze the consequence, of market power, i.e., who initiates it and who suffers from it [12]. Despite this advantage, a centralized pool-based model has a principle drawback related to the fairness across

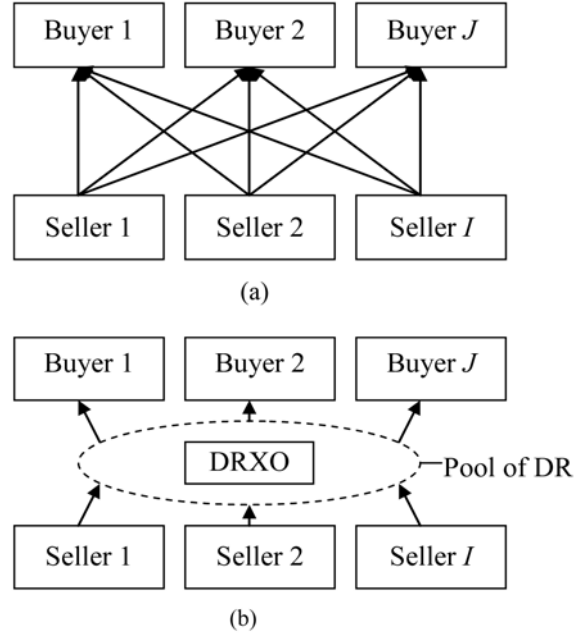


Figure 2.5: Fundamental models for DRX: (a) Bilateral; (b) Pool-based

all players. That is, the model sometimes cannot find the best trading option for each individual player within a reasonable computational time, due to huge amount of market data to be analysed centrally. Lack of fairness among market participants may undermine their motivation for self improvement to compete well each other in the same market. In order words, the pool-based model does not promote free market competition.

This section, for simplicity, only provides a fundamental view of those market models. Technical details will be investigated in subsequent chapters.

## 2.4 Practical implications of the DRX

Here we determines whether the proposed DRX approach represents a *new* and *separate* market for trading DR, and if yes then what is its relationship with the existing markets within a restructured power system? Our discussion is still at a theoretical level while the actual implementation of DRX is beyond the scope of this thesis.

### 2.4.1 DR versus electricity

Creating a DRX means that DR as market resource is conceptually separated from electricity. Such a separation has already been demonstrated to be feasible [64]. While electricity is the major resource to be managed within the physical networks and electricity markets, DR is an additional (minor) resource which is integrated to improve reliability of both net-

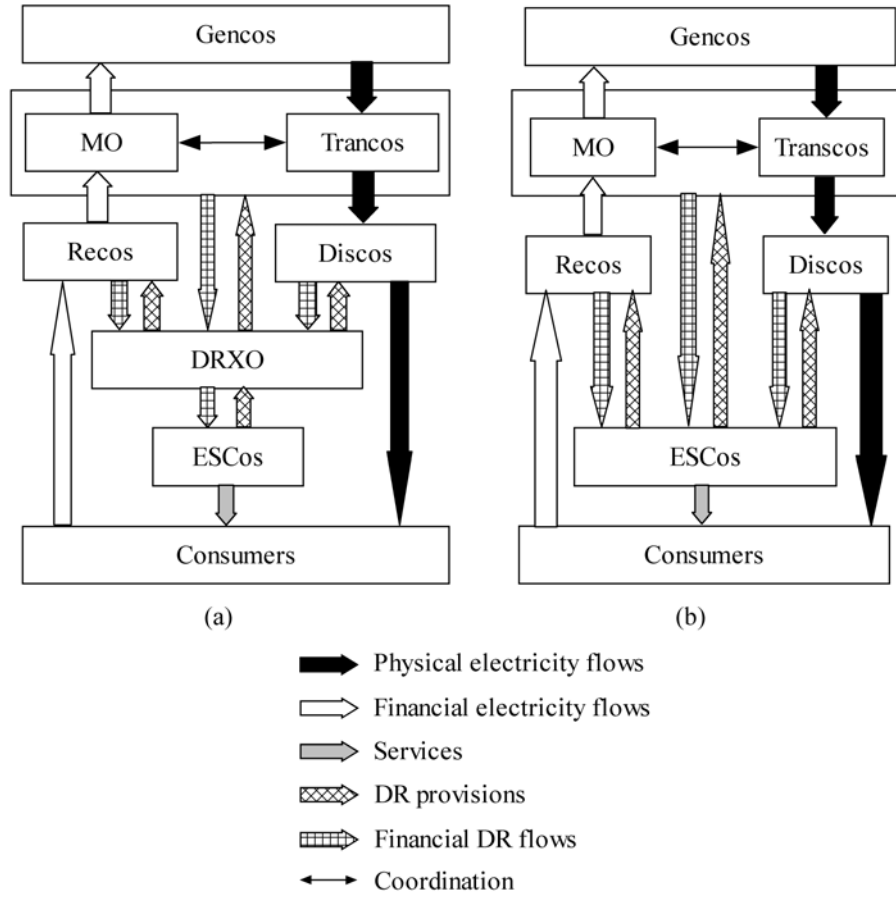


Figure 2.6: Modified power system structure with: (a) pool-based DRX model; (b) Bilateral DRX model

works and markets. In the next chapter, we will show that DR can be treated as a *public good* which refers to a special type of resources with each single unit jointly consumed by multiple independent players.

An integration of a DRX into the power system structure in Fig. 1.1 of the previous chapter will yield a *two market domain* system shown by Fig. 2.6. Here there are two market domains, electricity and DR. Within the former domain, electricity is managed as both a physical resource delivered by networks and a financial resource exchanged in the markets. Within the latter domain, DR provided by sellers (ECSos) is supplied to buyers (Transcos, Discos and Recos).

## 2.4.2 DRX versus existing electricity markets

This section discusses relationship between the proposed DRX market and those which have been well-established in the restructured power system. As shown in Table 2.3, such existing markets include [12], [6]: 1) those for trading electricity as primary resource on various timescales (i.e., hour-ahead, month-ahead, etc); 2) those for trading (secondary)

flexibility resources (i.e., generation reserve) on top of the electricity markets; 3) those for trading the right of using transmission, and/or distribution, networks; and 4) those for trading “greenness” derived from renewable power generation, i.e., Renewable Energy Certificates (REC). Together these existing markets constitute an exchange economy in a deregulated environment.

Table 2.3: List of markets within a restructured power system

Markets	Products	Sellers	Buyers	Timescales
Wholesale forward market	Electricity	Gencos	Recos and Large customers	Year-ahead or Month-ahead
Retail forward market	Electricity	Recos	Small businesses and Households	Year-ahead or Month-ahead
Wholesale spot market	Electricity	Gencos	Recos and Large customers	Day-ahead or Hour-ahead
Reserve market	Generation reserves	Gencos	Transcos	Minute-ahead or Second-ahead
<b>DRX market (proposed)</b>	<b>DR resources</b>	<b>ESCos</b>	<b>Recos, Transcos, Discos</b>	<b>Hour-ahead (intended)</b>
Transmission right market	Network usages	Transcos	Gencos, Recos, Large customers	Any timescale
REC market	RE certificates	RE-based Gencos	Investors Customers	Any timescale

As an addition to this economy, DRX as another type of flexibility trades can be placed at the same business level with the reserve markets [64]. While reserve refers to output adjustment of fast-responding generators on top of nominal power supply, DR is load adjustment on top of electricity consumption by end-users. This similarity means that both markets for DR and reserve are secondary to the electricity markets. The former aims at improving the reliability and efficiency of the latter, and are independent of other secondary markets such as the markets for greenness or network usages.

Within the exchange economy, players have different roles for different markets. For example, electricity customers buy electricity from the retail market and sell DR to the DRX market; Transcos and Discos provide network services and buy DR for their network reliability management. None of these entities plays a central role of managing the whole economy that is rather supervised by government delegates, i.e., the regulator, the energy MO, the ISO, and the DRXO. These bodies act for public interest which generally ensures fairness across all market participants by eliminating sources of market manipulation and enhancing market efficiency.

### 2.4.3 Timescale

An important operational issue for any DRX market relates to scheduling timing. Since the DRX is to be synchronized with the existing markets in a power system, the time frame of DRX must coincide with that of the system. Although both time frames could be divided into different time scales such as day ahead, hour ahead, real time, etc [64], this thesis addresses only the hour ahead timescale that is just before a “gate closure” (i.e., the time interval in which both electrical energy trading and DRX must halt for the ISO and Transcos to balance the whole power system using available generation reserves [64]). Operating the DRX on this time scale also provides Recos with increased flexibility to adjust the electricity demand of their customers by buying DR before the trading gate is closed. In summary, the DRX is considered to operate synchronously with the existing hour-ahead electricity markets in a power system.

### 2.4.4 Interactions between DRX and other markets

The interaction between various markets including the DRX is a complex issue. It occurs whenever prices of different products in different markets relate to each other due to “re-locating” these products. For example, if the Transco has enough reserve for maintaining network security, it would not purchase DR to be used for the same security purpose. In this case, the reserve market goes up by which reserve price increases due to the increased reserve demand, while the DRX market goes down with DR price decreased because less people are going to buy DR.

Study of the interaction between DRX and other electricity markets entails analyzing all economic, social and political aspects of the exchange economy. From an economic point of view, one should evaluate the relative potentials of various markets, in the sense that those markets which are more important than others are allowed to go up to enhance the overall benefit for the economy. The potentials evaluation for each market is generally based on a pricing consideration under demand-supply balancing, transaction costs, and other important economic conditions.

From a social perspective, one should determine welfares for different groups of customers having different levels of consumption flexibility. In general, those inflexible customers (i.e. disable or old) for whom electricity consumption is vital should be subsidized by which they are offered less expensive electricity and do not have to curtail loads for providing DR. Such subsidies, however, will be likely to down all relevant markets where the inflexible customers are involved in.

From a political perspective, one may have to consider interventions exerted on different markets by the government. Such interventions are to serve certain complex political goals that is, however, beyond the scope of this thesis. In general, any market experiencing more

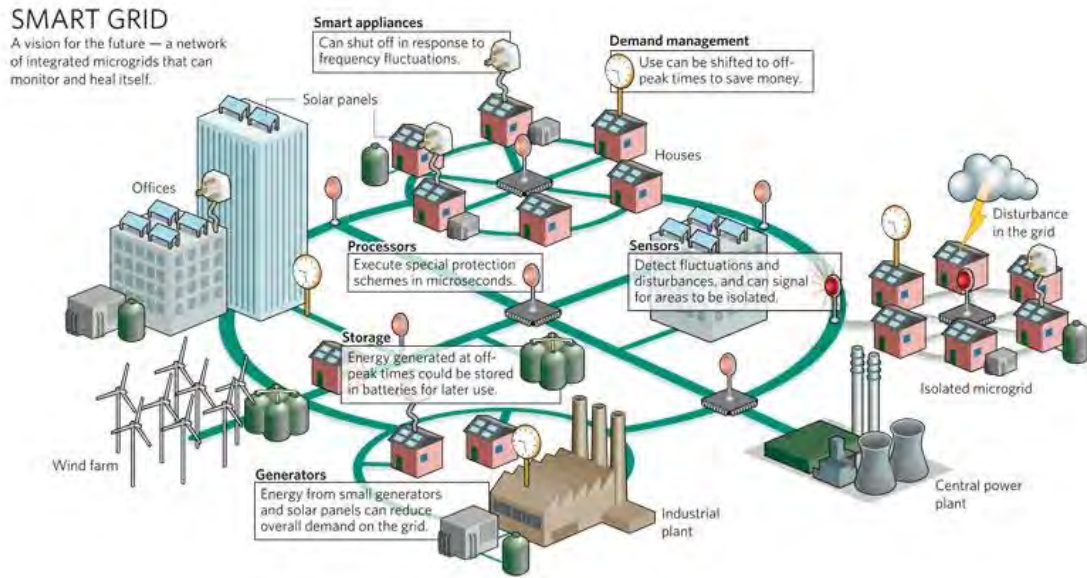


Figure 2.7: A conceptual illustration of smart grid [69]

government interventions than other markets becomes less competitive and consequently goes down.

Ideally, achieving an optimal outcome of DRX-based markets interaction requires an optimal balance between these three essential dimensions of the economy (i.e., economic, social, and political).

## 2.5 Implementation

Here we discuss the implementation aspect of DRX, with a specific focus on IT infrastructure development required for load control and communication between end-use customers and each electricity stakeholder including ESCos, Recos, Transcos and Discos. This infrastructure should also be able to promote the interoperability among those players and then to support the operation of a comprehensive DR scheduling/trading scheme like the DRX markets. Such a global communication system will expectedly be fully implemented soon in many countries as part of the so-called “smart grid” development campaign.

In general, the smart grid concept can be viewed as a modernization of the existing electricity grids (see Fig. 2.7). It is developed by integrating advanced communication and control technologies with power system operation on various timescales ranging from day-ahead, through hour-ahead down to real-time [68]. In this vision, a smart grid has the following functionalities (from the electricity supply view):

1. Enhancement of reliability
2. Reduce peak demand,

3. Shift usage to off-peak hours,
4. Lower total energy consumption,
5. Actively manage electric vehicle charging,
6. Actively manage other usage to respond to solar, wind, and other renewable resources, and
7. Buy more efficient appliances and equipment over time based on a better understanding of how energy is used by each appliance or item of equipment.

From a demand-side view, smart grid provides the following features:

1. Smart meters,
2. Dynamic pricing,
3. Smart thermostats and smart appliances,
4. Real-time and next day energy information feedback to electricity users,
5. Usage by appliance data, and
6. Scheduling and control of loads such as electric vehicle chargers, home area networks (HANs), and others.

Smart grids are currently promoted by many governments around the world. It reflects the need for digitally upgrading existing electricity networks which have been “cursed” by the public as a high-carbon, high-cost, low-efficiency, and low-tech delivery system. While these issues will remain controversial in the power engineering community, there is a sure argument that a well-implemented smart grid will strongly link a power utility company with its electricity consumers, helping them participate actively in the market and network operations of a power system. In this regard, we believe that the smart grids, if they are successfully implemented, will support the operation of our DRX schemes which is viewed as part of demand-side participation. The assessment of such grids are, however, beyond the scope of this thesis.

## **2.6 Summary**

This chapter explained the need for DRX as a new and separate market for trading DR in restructured power systems. In our opinion, creating such a market is somewhat controversial and thus entails substantial discussion regarding its feasibility. The way we took to examine such necessity and feasibility is summarised as follows.

In Section 2.2 we reviewed the existing works for scheduling DR, including those implemented and those currently under consideration. Here we surprisingly observed that most of the works constitute only partial scheduling solutions considering DR benefits for only a subset of market participants, either Transcos, Discos or Recos. This problem indicates lack of coordination across all DR-involved parties, and this could be seen as

the main reason for inefficient DR scheduling followed by low capacity utilizations, as has been seen in the real markets. This motivates the development of a comprehensive and fair DR scheme considering benefits across all stakeholders.

The most interesting observation in Section 2.3 is that, when we considered all players together including those who need DR and those capable of supplying it, we saw the possibility of setting up a new market. Then we proposed the DRX concept, where DR is treated as market resource to be exchanged between buyers and sellers. Buyers, including Transcos, Discos, and Recos, request DR and pay for it. Sellers, including ESCos on behalf of their electricity customers, supply DR as a source of income.

In section 2.4, we explained why we believe DRX can be a *separate* market in reality. That is, since DR is separated conceptually from electricity, a market for trading DR can be considered to be independent of the existing electricity markets within a restructured power system. Despite this resonable argument, we would not oppose a possible reconciliation of the DRX and other markets if this is actually necessary. Such a reconciliation could be in the form of a co-optimization model maximizing the total benefit of utilizing all resources supplied by multiple markets including those for electricity, DRX, generation reserves, etc.



## Chapter 3

# Pool-based Market Clearing

### 3.1 Overview

This chapter develops a particular type of market clearing model for DRX, namely pool-based, where all DR resources supplied by sellers are aggregated into a virtual pool handled by the DRXO, and all buyers have to access this pool to purchase needed DR. The motivation behind developing this model is to formalize the proposed DRX concept and to demonstrate its advantages over existing partial DR scheduling approaches. Numerical simulations are provided to support key arguments.

Microeconomic theory is applied to formulate the proposed pool-based market clearing model, with the aim of calculating both optimal price and quantity of a DR to be scheduled during the period under consideration. Particularly the calculation maximizes total market benefit for all participants under certain economic constraints such as demand-supply balance and contribution of each individual buyer to the total DR payment.

Throughout the market development, all mathematical notations of variables included in a DRX model are explained carefully. Most of them will be used again for the modeling and analysis in subsequent chapters.

The chapter is organized as follows. Section 3.2 defines the concepts of economic pool and market clearing, and explains their implications for a DRX. Section 3.3 formulates a pool-based optimization model to clear the DRX market. Section 3.4 presents a numerical study followed by some concluding remarks in Section 3.5.

### 3.2 Pool-based market concepts

#### 3.2.1 Economic pool

“Pool” is an important concept in economics, accounting and finance [5, 9]. Generally it refers to aggregation and valuation of all market resources (assets, equipment, personnel,

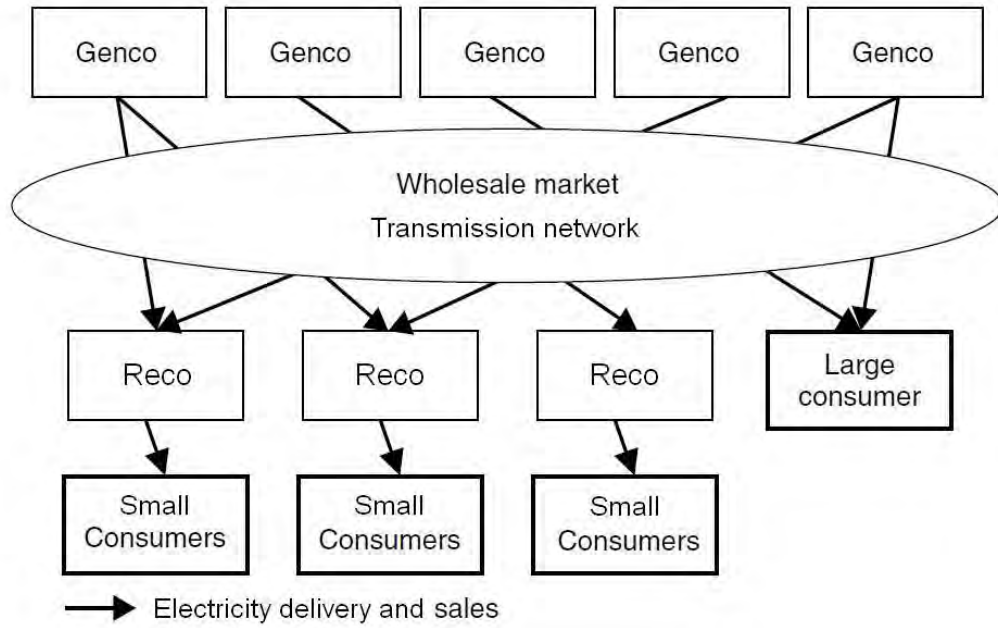


Figure 3.1: Electricity pool

services, etc) having a common point of interest to market participants, with the main aim of maximizing total benefit and/or minimizing total risk associated with resources provision and utilization.

Wholesale electricity markets represent a good example of the pool concept [6,12]. As shown in Fig. 3.1, bulk electricity produced by Gencos at certain locations of a transmission network is aggregated and delivered throughout the network to large customers and Recos serving small customers via retail contracts. This centrally operating paradigm aims at maximizing total benefit of trading electricity while maintaining transmission network security by accepting only feasible trades, for instance, without violating physical network constraints. If the security is threatened, cascading failures followed by a system blackout may occur, causing electricity trades to be delayed and an entire region to be unsupplied for many hours. Such intolerable security risks make pooling a dominant approach for operating the wholesale electricity markets. As an alternative approach, bilateral transaction where electricity is traded independently between every two market players (a Genco and a Reco) has been considered, but is not yet implemented due to its limitation associated with lack of network security consideration [52].

In addition to electricity markets, pooling techniques have been used extensively in finance [9, 73], where individual (underlying) assets such as credit cards, auto loans or mortgage loans are aggregated using a (common) financial mechanism called “securitization”, with the aim of evaluating total risk associated with investing in all assets. As an outcome of pool-based securitization, new financial products termed “security” represent-

ing different portions of the total risk are created and then sold to investors who want to make profits by raising funds. In this case, pooling assets helps diversify their collective risk, and thereby, making an efficient cash flow across the whole financial security market.

This chapter utilizes the pool concept to develop a DRX in which DR is considered a market resource traded between sellers (including ESCos on behalf of their customers) and buyers (including Transcos, Discos and Recos). Here pool plays the role of being a virtual marketplace where all DR resources produced by electricity customers are aggregated and valued together and where all buyers can easily seek needed DR.

Pooling has significant implications particularly for the DRX operation as it represents a trading interface between small customers and DR buyers. In fact, individual DR produced by a single customer is not tradable, because it cannot match buyer requirements that are at aggregated levels. For example, the Transco generally requires DR from customers in groups (corresponding to different load points at transmission level), but do not need to know exactly which customers are the providers [54]. In which case, aggregating individual DR resources into larger units following buyer requirements will improve the tradability of the products. This aggregation can be performed via resources pooling.

Since DR is separated conceptually from electricity, a pool of DR can be considered to be independent of the existing electricity pool in a wholesale market given above. Indeed, they are very different business procedures—the former provides a grouping together of individual DR resources (provided by small customers) while the latter packaging electricity (produced by Gencos) for centralized trades constrained by network security management. Nevertheless, these pools could be combined together into a joint market, for the purpose of co-optimizing benefits and/or minimizing risks associated with providing all resources including electricity and DR. A similar situation has been observed within the electricity market itself, where individual markets including those for trading electrical energy and those for trading generation reserve on top of this energy can be co-optimized, in the sense that the overall cost of supplying these resources minimized [51].

In general, pooling promotes efficient resource allocation by selecting the best resource units which offer more benefit and/or less risk than other units from the same pool. For example, the electricity pooling described in Fig. 3.1 can always extract those power sources offering lowest generation cost under given network security constraints. Similarly in a pool-based DRX, all DR units from customers are valued together, with the aim of choosing the best units providing significant benefits for the buyers (Transcos, Discos and Recos) while requiring relatively low payments from them. This advantage essentially improves the competitiveness of the proposed DRX approach compared with conventional partial approaches described in previous chapter.

The drawback of pooling is that it incur transaction cost that is the cost of aggregating and valuing all resources. In an electricity market, such a cost also include the monetary

amount spent on maintaining transmission network security. Allocating transaction cost fairly among market participants is a challenging task entailing significant efforts of the market operators [12].

### 3.2.2 Market clearing mechanisms

While pooling aggregates all individual products for the evaluation purpose, market clearing guides the buyers to purchase needed products at competitive prices. Formally market clearing is the process of getting all supplied products meet buyer demands via price adjustment [8]. The term “demand” here refers to requirement for both quality and price of a product, for instance, low quality products should not be expensive. With the quality pre-determined via resources pooling and valuation, the price can be adjusted accordingly during the market clearing process.

Table 3.1: Examples of market clearing

Types	Examples
Physical/ Geographical	Supermarkets, shopping malls.
Electronic/ Internet-based	eBay ( <a href="http://www.ebay.com/">http://www.ebay.com/</a> ), Amazon ( <a href="http://www.amazon.com/">http://www.amazon.com/</a> ).
Automatic/ Computerised	Electricity markets, Ancillary service markets, Demand Response eXchange.

In traditional sense, market clearing is taken place in a geographical area where buyers and sellers gather to negotiate products. Prices are frequently revised so that the entire supply (at given product quality) can be sold to the buyers. Supermarkets providing food and household merchandise are examples of physical market clearing, as given in Table 3.1. With the advent of computers and Internet, many markets have been moved to virtual environments where information circulates electronically and trades are cleared with only a click of mouse. eBay and Amazon are examples of electronic markets. Despite these technological changes, human still plays the main role of decision making in a market clearing process. For many commercial systems working in real time, needed resources must be supplied instantly from relevant markets. This entails *online* clearing tasks that could be beyond human capability and therefore are undertaken automatically by computers.

Wholesale electricity markets give a good example of automatic market clearing, where electricity demand and supply—generation and load—must be balanced on a *second-by-second* basis, as given by Fig. 3.2 [12]. A significant mismatch can lead to such consequences as market failure followed by a system blackout. Unfortunately electricity price alone, unlike

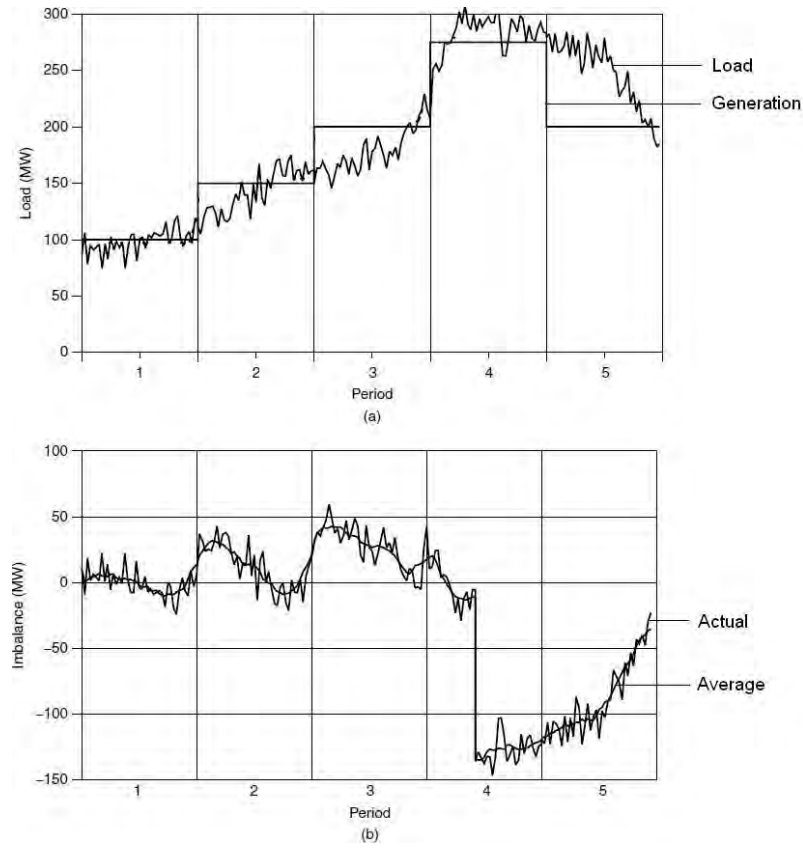


Figure 3.2: (a) Real time fluctuations of generation and load; (b) Imbalances resulting from these fluctuations

those in other markets, is not enough to secure short term demand–supply balance. This problem can be explained because most customers are unable to adjust their consumption following real-time price signals, similarly many generating units cannot boost their outputs quickly in response to unexpected shortfalls of power supply. To compensate for this limitation of electricity market clearing, ancillary services (AS) has been used which refers to quick adjustments by some flexible generating units (for instance, gas turbines) using their *available* supply capacity [6]. In addition to AS, DR by flexible customers can also be utilized by the Transco for the same balancing purpose.

The market clearing concept is central to developing a pool-based DRX model. Here automatic approach with DR to be traded online is applied. Specifically all DRX transactions are cleared centrally by a dedicated computer playing the role of being a market operator (DRXO). This market clearing model uses input (demand and supply) data automatically collected from DR buyers (Transcos, Discos, and Recos) and sellers (ESCOs on behalf of their customers) via an Internet-based communication system. In this regard, there is no need for creating a physical marketplace for the proposed DRX, which reduces its implementation cost and thus enhances its economic viability.

As with other markets, DRX market clearing aims at matching buyers demand with sellers supply. Here “demand” represents requirement for both quality and price of a DR, while “supply” giving the product availability. Balancing demand and supply in general is not difficult, but balancing *optimally* could be a challenging task. It entails maximizing the total benefit created from trading DR across all market participants. In order words, the market clearing task should be represented by a profit optimization problem subject to demand-supply-balance constraint. This problem will be given later in this chapter.

As similar to the pools, clearing DRX market can be independent of the electricity market to the extent that they represent unsynchronized processes working in parallel. While the later delivers electricity from Gencos through Transcos and Discos to customers, the former supplying DR from the customers back to those players for their risk management benefits associated with the electricity delivery.

Parallel market clearing for multiple resources represents the current trend in operating power systems from an economic perspective. Its advantage is to enhance competition across all market participants. Specifically each player needs to be more responsive to producing or utilizing market resources, by monitoring production costs more closely and/or purchasing resources on the basis of competitive prices. Another advantage of introducing parallel markets is innovation where participants have to develop new methods or technologies for problem solving which promises them—the innovators a competitive edge [12]. Additionally markets parallelism effectively delivers a wide range of services ranging from electrical energy through ancillary services (or generation reserves) down to DR resources, which together increase the flexibility and reliability in power systems operation.

Despite these advantages, parallel market clearing incur high transaction costs associated with running each market separately. It may also lead to some undesirable situations including “price reversal” problem observed in the California electricity market [24, 26]. This problem refers to cases where wholesale electricity price is forced back to the “nominal” value during peak demand but automatically increases again in other periods, as a result of clearing other markets, for instance, the market for ancillary services. Nevertheless, we keep the issues of high transaction cost and electricity price reversal as open questions for future research.

### 3.3 Market clearing optimization model

#### 3.3.1 Overall description

With reference to the above economic concepts, the whole procedure for pool-based DRX market clearing is described in Fig. 3.3. It includes several operational stages reflecting different requirements for scheduling DR *from a practical point of view*. These stages are

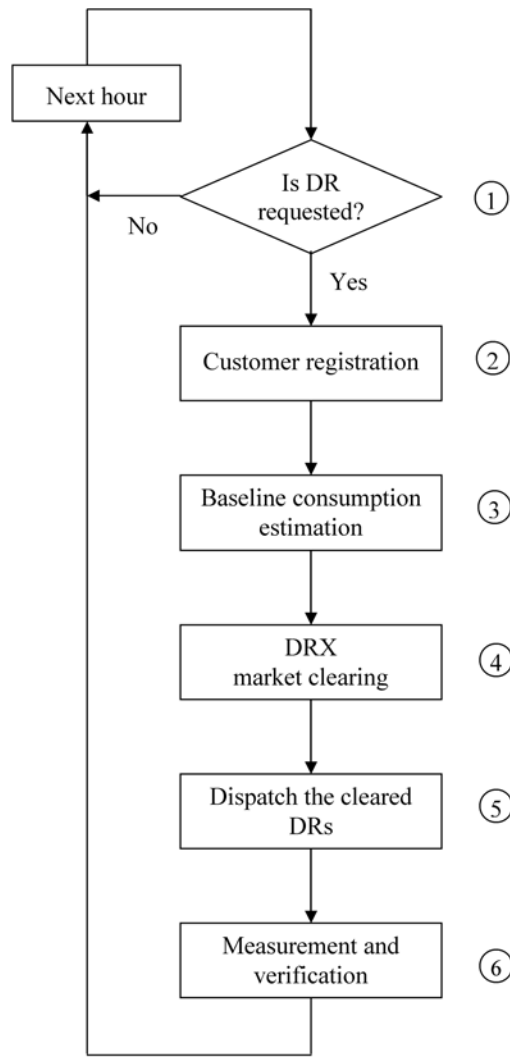


Figure 3.3: Flowchart for clearing a DRX market

coordinated centrally by the DRXO using data collected from market participants, who either request or supply DR resources. The proposed market clearing procedure operates on an hourly basis, to synchronize with the common timeframe of economic dispatch in the power system.

Stage 1 is rather simple waiting for *any* market participant among the Transco, Discos and Recos to request DR from electricity customers during a given hour. Such a request is made as the participant needs a certain amount of load reduction to deal with its peak demand problems relating to electricity market volatility or power network reliability. For example, when the Transco and Discos foresee network outages, they could impose load curtailment to mitigate the outage consequences. Similarly a Recos may anticipate some upcoming spikes of the wholesale electricity market price and thus have to reduce customer demand by requesting DR. Note that not (necessarily) all participants want DR in a given

on-peak hour, but if none of them requesting, all subsequent tasks of the DRX market clearing (see Fig. 3.3) would not be undertaken for that hour.

Following buyer requests, those electricity customers capable of curtailing loads register to sell DR on the market. This registration is voluntary as it is decided by the customers on their own free wills. In the case that no customer register, no DR is available for supply and consequently the market would not be cleared. This case, however, is rare since there are always customers interested in selling DR as a source of income [27]. Then the market clearing can be preceded by matching this supply availability with buyer demands.

For those customers registering for selling DR, their “baseline” electricity consumption will be estimated by the DRXO (see Fig. 3.3, stage 3). This consumption refers to the amount a customer would *normally* use, and is considered for calculating DR in the form of load curtailment during peak demand. Generally estimating the baseline consumption entails considering both load forecasting and baseline manipulation issues.

### **Electricity load forecasting**

Forecasting is vital part of business planning in today’s competitive electricity markets. Many operating decisions are essentially based on load forecasts, i.e., dispatch scheduling of generating capacity, reliability assessment, and maintenance planning for the generators, as well as DRX market clearing. While much work has been done for forecasting aggregated loads coming from customers in groups, less attention being paid to individual customers [68]. Without an accurate individualized prediction model, not only DRX but also other scheduling programs involving small customers will not work realistically.

Forecasting individual loads are generally more difficult than at aggregated levels [72]. This can be explained by *abnormal* electricity consumption (such as when the consumer is on vacation), which bias analysis of historical consumption behavior, and thus significantly decrease the prediction accuracy (note that at aggregated levels, such abnormality effects are dominated by the large number and the geographical dispersion of customers, as per central limit theorem in probability theory.) To deal with this forecasting problem, anomaly detection has been developed using statistical techniques such as regression-based, entropy-based, and clustering-based [74]. These anomaly detection methods could be incorporated within conventional load forecasting models, to deal with the inherent uncertainty in individual consumption behaviour.

### **Baseline manipulation**

The above load forecasting techniques are typically used by an electric utility company having insufficient consumption data from private customers [74]. To be more realistic in forecasting while preserving privacy, each customer can estimate their own consumption and send this information back to the utility. In this scenario, load prediction will definitely be improved, but it could be vulnerable to baseline manipulation where the customers “lie



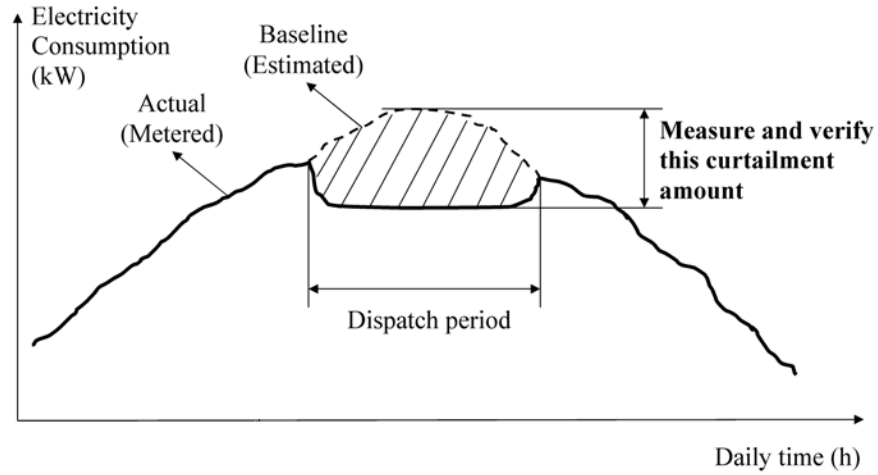


Figure 3.4: Verifying DR dispatch by a customer

on purpose” by declaring overestimated baseline consumption, with the aim of claiming more load curtailment than the actual amount and thus illegitimately increasing the monetary compensation. No doubt, this baseline issue has to be addressed properly for reliable and accurate load forecasting, but is beyond the scope of this thesis.

Following baseline estimation for electricity customers registering in DR supply, the market can be cleared centrally by the DRXO using an optimization model (to be developed in next subsections.) Then DR will be dispatched virtually by which the customers switch off their loads.

The final step in Fig. 3.3 is measurement and verification to ensure that customers have supplied right amounts of DR following above market clearing results. These tasks are illustrated in Fig. 3.4, where the load curtailment amount representing DR is measured as the difference between baseline (estimated above) and actual consumption which can be metered using a telemetry system called “Advanced Metering Infrastructure” or simply AMI installed on the customer site and communicating with the host utility company [22]. There are many AMI standards developed by different hardware manufacturers over the world. These are characterized in terms of core functionalities and implementation costs as of Table 3.2 (see [68] for a comprehensive review). Since these AMI technologies have been successfully tested by many utilities in North America, Europe, and Australia, they can be utilized for DRX operation generally, and dispatch measurement and verification in particular.

In the following we use *microeconomic theory* defined in [5, 6, 75, 77–79] to develop the core optimization model for DRX market clearing given by step 4 in Fig. 3.3. For the sake of simplicity, we defer discussion of the background theory until required during the analysis.

Table 3.2: Some well-developed AMI standards

Name	Countries
open Automated Demand Response (openADR)	U.S.A (i.e., California.)
Google PowerMeter	U.S.A, Australia, Europe.
ZigBee/HomePlug	Australia,
Smart Energy Profile	Europe.

### 3.3.2 DR quantity and price as decision variables

Here we formalize the notion of DR resource in terms of quantity and price as core market parameters. They will be considered decision variables, that is, the variables to be jointly controlled by decision makers such as DRXO, buyers and sellers for the purpose of optimizing the resulting market benefit derived from pool-based DRX clearing followed by DR dispatch. Since DR is measured as the difference between the baseline ( $C_{\text{baseline}}$ ) and actual consumption ( $C_{\text{actual}}$ ) of a customer, a DR quantity ( $x$ ) is given by

$$x \triangleq C_{\text{baseline}} - C_{\text{actual}} \quad (3.1)$$

Unlike many other markets using a single price across all market participants (for instance, the uniform price in wholesale electricity markets [6]), the DRX consider multiple prices for trading different DR quantities—each associated with certain buyers or sellers. Together these quantities represent the whole set of DR resources need to be cleared within a DRX market corresponding to a restructured power system.

For clarity, we define DR quantities and prices for *each* type of DR sellers and buyers, and then aggregate all these decision variables into a common pool for optimization-based market clearing. Let  $\mathcal{I}$  denote the set of DR sellers (i.e., ESCos on behalf of their electricity customers), where  $I \triangleq |\mathcal{I}|$  denotes the number of these sellers. (Note that the symbol  $\triangleq$  means “defined as” or “equal to”). For each seller  $i \in \mathcal{I}$ , let  $\mathcal{L}_i$  denote the set of customers represented by the seller, with  $L_i \triangleq |\mathcal{L}_i|$ . Then, we define an *individualized supply quantity vector* as follows:

$$\mathbf{x}_i \triangleq [x_{i,1} \ x_{i,2} \ \dots \ x_{i,L_i}] \quad (3.2)$$

where each positive scalar  $x_{i,l}$  denotes a quantity (in MWh) of DR in the form of load curtailment provided by an individual customer  $l \in \mathcal{L}_i$ . In this case, we can define an *individual marginal cost vector* as follows:

$$\mathbf{c}_i \triangleq [c_{i,1} \ c_{i,2} \ \dots \ c_{i,L_i}] \quad (3.3)$$

where each positive scalar  $c_{i,l}$  denotes a marginal cost (in \$/MWh) of DR provided by customer  $l \in \mathcal{L}_i$ , corresponding to individual quantity  $x_{i,l}$ . Clearly, the cost vector  $\mathbf{c}_i$  is a function of the quantity vector  $\mathbf{x}_i$  (i.e.,  $\mathbf{c}_i = \mathbf{C}_i(\mathbf{x}_i)$ ). Such a function refers to a *supply curve* to be submitted by seller  $i$  to the DRX market. Intuitively, as supply represents the capability of providing DR by a seller, supply curve gives the provision cost at various DR levels (quantities). This cost is incurred by the electricity customers due to inconvenience resulting from load curtailment.

Defining individual DR quantity has the advantage of characterizing specific economic circumstance of each customer in a DRX. Such characterization would give both individualized costs of supplying DR and resulting monetary compensations for the providers. Specifically those incurring higher DR costs deserve a larger share of the compensations. This advantage improves fairness across all DR customers, as will be analysed in Section 3.4 via numerical simulation.

To define the other side of the market, let  $\mathcal{J}$  denote the set of DR buyers (i.e., Recos, Transcos, Discos), where  $J \triangleq |\mathcal{J}|$  denotes the number of these buyers.

Unlike sellers, DR buyers are only interested in *aggregated* quantities. Buyers demand an amount of DR from a group of customers but might not want to know exactly which customers were the providers [80]. To illustrate this aggregation idea, we consider a small but comprehensive power system as in Fig. 3.5.

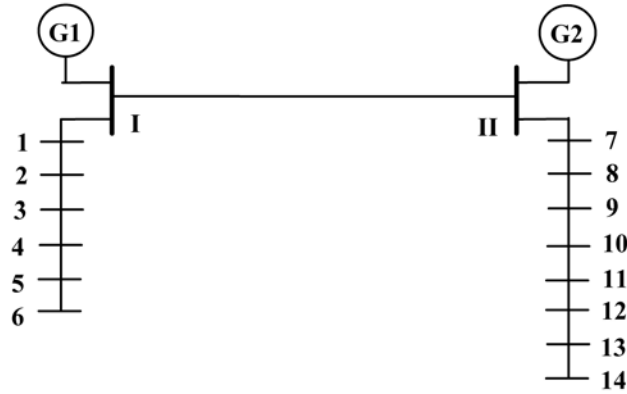


Figure 3.5: Small power system for demonstrating customers aggregation. Here each feeder load point (1, 2,...,14) supplies power for a small geographical area such as suburbs

This power system includes both transmission and distribution levels corresponding to a wholesale and a retail electricity markets, respectively. The 2-bus transmission network is operated by a Transco, while the distribution (comprised of 2 feeders connecting to these buses) by a Disco. There are also a Reco and an EScO, each deals with all electricity customers. These arrangements reflect the current practice of restructured power systems [6, 12]. Formally  $\mathcal{I} = \{\text{EScO}\}$ —the set of DR sellers and  $\mathcal{J} = \{\text{Transco}, \text{Disco}, \text{Reco}\}$ —the set of DR buyers.

In this small system the Transco purchases aggregated DR quantities from two different groups of customers—one includes customers within bus I and the other within bus II of the transmission network. Each aggregated quantity is given by the sum of individual quantities from corresponding customers within a group. This aggregation is practically essential as it simplifies customer management task. Rather than considering all individual customers (millions of them in practice), the Transco only needs to map them into a limited number of load points (i.e., I and II in Fig. 3.5) at the transmission level. Similarly the Disco can group the customers based on their geographical positions within a distribution feeder. In which case, there would be one group of customers connecting with load point 1, one with load point 2, ..., and the last one with load point 14 of the distribution networks in Fig. 3.5. Different from the Transco and Discos, Recos may have their own way of grouping the customers according to the underlying structures of retail electricity contracts. For example, customers holding the same type of contracts with a Reco can be arranged in one group. Such types are generally given by specific terms and conditions of the contracts, i.e., forward electricity price and volume to be supplied to the customers in a given future date.

Consequently, each DR buyer involves a *set* of customer groups. However different groups associated with different buyers may overlap as they may have mutual customers. This is because each customer considered at the transmission level, must also be considered at the distribution level, and furthermore has a supply contract (as has been illustrated in Fig. 3.5). Therefore, this customer is included in three different groups associated with three corresponding buyers (i.e., a Transco, a Disco, a Reco), creating an overlap between these groups.

For each buyer  $j \in \mathcal{J}$ , let  $\mathcal{N}_j$  denote a set of customer groups being associated with the buyer, where  $N_j \triangleq |\mathcal{N}_j|$ . As an example, the Transco in Fig. 3.5 has  $\mathcal{N}_{\text{Transco}} = \{\text{I}, \text{II}\}$ , while  $\mathcal{N}_{\text{Disco}} = \{1, 2, 3, \dots, 14\}$ . Then we define an *aggregated demand quantity vector* as follows:

$$\mathbf{y}_j \triangleq [y_{j,1} \ y_{j,2} \ \dots \ y_{j,N_j}] \quad (3.4)$$

where each positive scalar  $y_{j,n}$  denotes an aggregated quantity of DR that buyer  $j$  wants to buy from a customer group  $n$  as a whole. In this case, we can define an *aggregated price vector* as follows:

$$\mathbf{p}_j \triangleq [p_{j,1} \ p_{j,2} \ \dots \ p_{j,N_j}] \quad (3.5)$$

where each positive scalar  $p_{j,n}$  denotes a marginal price (in \$/MWh) of DR, at which buyer  $j$  is *willing* to buy from customer group  $n$  at corresponding aggregated quantity  $y_{j,n}$ . Clearly, the price vector  $\mathbf{p}_j$  is a function of the quantity vector  $\mathbf{y}_j$  (i.e.,  $\mathbf{p}_j = \mathbf{P}_j(\mathbf{y}_j)$ ). This function refers to a *demand curve* submitted by buyer  $j$  to the DRX market. Intuitively,

while demand represents buyer desire for using DR, demand curve gives preferred prices for the product to be purchased at different quantities. These prices usually correlate with risk management benefits for buyers (Transco, Disco and Reco) using DR. That is, those products giving higher benefits should be more expensive.

The formalisation of DR quantities, prices, and demand and supply curves is novel part of this thesis over the existing market literature within power engineering. Nevertheless, it follows the notion of market clearing defined by microeconomic theory [75], and further realises the pool concept by aggregating DR quantities for each buyer in the market but keeping such quantities individualized for the sellers.

### 3.3.3 Objective function

In a DRX market, the DRXO collects both aggregated demand and individualized supply curves from DR buyers and sellers, respectively. It then balances the overall supply given by  $\mathbf{x} \triangleq [\mathbf{x}_1, \dots, \mathbf{x}_I]$  with overall demand given by  $\mathbf{y} \triangleq [\mathbf{y}_1, \dots, \mathbf{y}_J]$  at overall market price  $\mathbf{p} \triangleq [\mathbf{p}_1, \dots, \mathbf{p}_J]$ , through a centralized calculation. Such a balancing procedure is market clearing [6, 75] for which the objective value (that is the value to be optimized) is identified in this section from a practical point of view.

Fig. 3.6 illustrates the market clearing process. For simplicity we consider the simplest case with only one DR quantity followed by one price in a small DRX market containing a buyer and a seller, while other cases with multiple quantities and multiple prices will be discussed later. As in Fig. 3.6 the demand curve from buyer is given by function  $P(\mathbf{x})$ . According to the *law* of demand,  $P(\mathbf{x})$  is downward sloping as the buyer is willing to pay higher price for additional quantity of a product (DR) when it has only a small amount of this product. Turning this around, the buyer will increase the total quantity to be purchased if the market price decreases [6]. The supply curve from seller, on the other hand, is given by function  $C(\mathbf{x})$  having upward slope which can be explained by the increasing marginal cost associated with increasing DR quantity to be produced. These demand and supply characteristics will be investigated further in Chapter 6.

In theory, the market clearing *objective* is to determine an equilibrium point which is in Fig. 3.6 the intersection of demand and supply curves,  $(\mathbf{x}^*, \mathbf{p}^*)$ , where not only supply meets demand but also marginal production cost is matched by price coming from the buyer. This equilibrium results in *Pareto* efficiency for the market, at which point the benefit for the buyer cannot be improved without reducing seller benefit [6]. In this case, the total market benefit, as depicted by the area  $(A + B + C + D + E + F)$  in Fig. 3.6, reaches the global maximum. If the market is cleared at a non-equilibrium point  $(\mathbf{x}, \mathbf{p})$ , the resulting total benefit becomes  $(A + B + C + D)$  which is sub-optimal.

In reality, clearing the market at its equilibrium point must rely on a number of economic conditions [75]. First, market participants (a buyer and a seller) are “price takers”

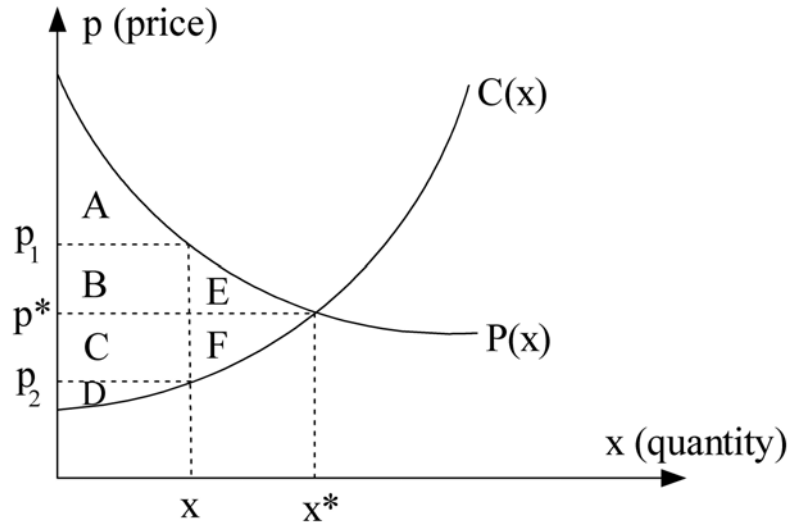


Figure 3.6: Market clearing model

in the sense that each of them involves trading a relatively small quantity compared to the total quantity being traded in the market. In this case their individual transactions have no influence on the market price. Such an idealized condition is only a standard for the market evaluation. In fact, real markets usually contains certain participants holding “dominant” market shares (compared with those for other participants) and therefore having the opportunity to influence the market price. This is the case of the 2002 California’s electricity market crisis, where some large Gencos including Enron took advantage of the unexpected supply shortages during peak demand to sell electricity at premium prices, sometimes up to a factor of 20 times its normal value [19].

The second equilibrium condition is market freedom, that is, the market is free from intervention, for instance, by the government. It is opposite to a controlled market where the government directly regulates how the product might be used, priced or allocated, rather than relying on the market clearing mechanism with demand–supply balancing. Electricity *retail* is a good example of controlled market, where the retail prices paid by small electricity customers is regulated by the government. As a consequence, the product allocation involving quantity and price is no longer at the market equilibrium.

There could be a conflict of interest between price taking and free market conditions towards competitive equilibrium. That is, the market freedom may be vulnerable to the price manipulation by those participants holding a dominant market share. For example, the pre-2002 California *wholesale* electricity market had been loosely regulated by the government, and as a result, the market crisis with “artificial” price increases occurred.

Due to these practical difficulties in finding competitive equilibrium, here we clear the DRX market using an alternative method—optimizing the total market benefit subject

to certain constraints, including the demand–supply balance and some other constraints related to individual participants. As a result, the constrained market benefit, as depicted by the area  $(A + B + C + D)$  in Fig. 3.6, should be slightly smaller than would be the case under market equilibrium [25]. This adverse effect of optimization-based market clearing will be investigated further in Section 3.4 via numerical study.

Mathematically, optimizing the total market benefit is given by:

$$\max \left\{ \sum_{j \in \mathcal{J}} B_j - \sum_{i \in \mathcal{I}} C_i \right\} \quad (3.6)$$

where  $B_j$  and  $C_i$  are the gross benefit for buyer  $j$  and the cost of producing DR by seller  $i$ , respectively. The difference between the total benefit  $(\sum_j B_j)$  and the total cost  $(\sum_i C_i)$  is equal to the total market net benefit—the value to be maximized. This calculation again can be illustrated by Fig. 3.6 for the simplest case of one buyer and one seller in a DRX market. Here the gross buyer benefit derived from DR is represented by the area under the demand curve  $P(x)$ , while the DR production cost by the area under the supply curve  $C(x)$ . For simplicity, we omit formal proof for this representation, but will consider it again in Chapter 6 via cost/benefit quantification.

Mathematically, both  $B_j$  and  $C_i$  can be calculated by integrating respective demand and supply curves:

$$B_j = \sum_{n \in \mathcal{N}_j} \int_0^{y_{j,n}} p_{j,n}(y_{j,n}) dy_{j,n} \quad \forall j \in \mathcal{J} \quad (3.7)$$

$$C_i = \sum_{l \in \mathcal{L}_i} \int_0^{x_{i,l}} c_{i,l}(x_{i,l}) dx_{i,l} \quad \forall i \in \mathcal{I} \quad (3.8)$$

From a practical perspective, this calculation is performed during the market clearing process and by the market operator using demand and supply data collected from buyers and sellers, respectively. Hence we assume that both sellers and buyers always submit their correct data reflecting their true costs and benefits given by (3.7) and (3.8). Otherwise, the objective value given by (3.6) would not be the true market net benefit but only a “perceived” value [42]. In Section 3.4, we will illustrate how this assumption could be reasonably satisfied under the DRX market clearing model developed here.

From the objective function (3.6) followed by (3.7) and (3.8), one can correctly deduce that clearing a DRX market via benefit optimization is independent of the existing electricity markets including wholesale and retail. Specifically the DRX market clearing objective value,  $\sum_j B_j - \sum_i C_i$ , has no parameter associated with the electricity trades in those markets. Such parameters may be either cost of producing electricity by Gencos or

benefit of retailing electricity by Recos, or benefit of electricity consumption by end-use customers. A comprehensive description of all electricity market parameters can be found in [6].

In fact, it is possible to combine the DRX clearing with electricity market clearing via co-optimization where all DRX parameters (such as demand/supply curves or cost/benefit data) and those of the electricity wholesale/retail markets are incorporated within a common objective function that is the value to be maximized for all markets together. Such a combined optimization model has the advantage of realising the implicitly strong connection between electricity and DR as two important market resources in the power system. However it entails significant computational effort due to very large number of parameters included. A similar computational problem has been observed within the electricity market itself [51, 76], where the simultaneous scheduling for reserve and electrical energy could result in a combinatorial “explosion”.

### 3.3.4 Constraints

Constraints need to be defined in the proposed market clearing optimization model. The most important constraint is demand–supply balance given by:

$$y_{j,n} = \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}_i} u_{i,l}^{j,n} x_{i,l} \quad \forall j \in \mathcal{J}; n \in \mathcal{N}_j \quad (3.9)$$

The left hand side of (3.9) represents aggregated quantity  $y_{j,n}$  which is the demand of buyer  $j$  over customer group  $n$ . On the right hand side, all individual quantities  $x_{i,l}$  of customers included in the group are added together to form an aggregated supply matching the demand. Binary coefficient  $u_{i,l}^{j,n}$  represents *relational status* of each customer  $l$  to the group  $n$ .  $u_{i,l}^{j,n}$  is 1 if the customer is included in the group, and 0 otherwise.

To illustrate this balancing equation, we consider again the power system in Fig. 3.5. For simplicity we assume that each load point at a distribution feeder level represents a single customer, therefore there are totally 14 customers in the system. We also assume that the Reco offers two different types of electricity retail contracts—type A for customers 1, 2, ..., 10 and type B for customers 11, ..., 14. Consequently we have  $\mathcal{N}_{\text{Reco}} = \{\text{A}, \text{B}\}$ ,  $\mathcal{N}_{\text{Transco}} = \{\text{I}, \text{II}\}$ ,  $\mathcal{N}_{\text{Disco}} = \{1, 2, \dots, 14\}$ , as well as  $\mathcal{J} = \{\text{Reco}, \text{Transco}, \text{Disco}\}$ . Note also that  $\mathcal{I} = \{\text{ESCo}\}$  and  $\mathcal{L}_{\text{ESCo}} = \{1, 2, \dots, 14\}$ . According to (3.9):

$$y_{\text{Reco},\text{A}} = x_{\text{ESCo},1} + x_{\text{ESCo},2} + \dots + x_{\text{ESCo},10}$$

$$y_{\text{Reco},\text{B}} = x_{\text{ESCo},11} + \dots + x_{\text{ESCo},14}$$

$$y_{\text{Transco},\text{I}} = x_{\text{ESCo},1} + x_{\text{ESCo},2} + \dots + x_{\text{ESCo},6}$$

$$y_{\text{Transco},\text{II}} = x_{\text{ESCo},7} + \dots + x_{\text{ESCo},14}$$



$$y_{\text{Disco},1} = x_{\text{ESCo},1}$$

$$y_{\text{Disco},2} = x_{\text{ESCo},2}$$

...

$$y_{\text{Disco},14} = x_{\text{ESCo},14}$$

Since customer  $l$  supplies a common DR to one Reco, one Disco, and the Transco, the customer is included in three different groups associated with these three DR buyers, respectively. Therefore, its quantity  $x_{i,l}$  appears in three corresponding balancing equations, as illustrated by the above example. This *repetition* shows that DR from a customer can be considered **public good**, which is a special type of resource with each single quantity jointly used by multiple players. Indeed, treating DR as a public good is central to the analysis of a DRX, not only in this chapter but also others within this thesis.

The next constraint is related to the contribution of each player in overall payment for the public good. These contributions can be specified in an *assurance contract* that is signed between involved players [77–80]. This contract refers to a financial mechanism for guaranteeing an efficient provision of the public good in the face of the **free riding** problem. In general, such a problem occurs whenever there is an *action* (i.e., scheduling DR as a public good) that would benefit several players (i.e., a Transco, a Disco, a Reco), but once the action is taken, there is no way to exclude those who did not pay for the action from the benefits. This non-excludability leads to free riding opportunity—some self-interested players may make a decision to let other players pay for the action, then to enjoy the benefits for free. This situation is unfair to the voluntary payers and reduces the overall benefit of taking the action. In the worst case where no player pays, the action would not be taken.

Assurance contract is considered a powerful mechanism to avoid the free-riding problem, that is, to encourage every beneficiary contribute to the overall payment of a public good. The core idea is to let the beneficiaries voluntarily *pledge* to contribute paying for the good. If the total payment is enough, the good will be supplied; otherwise, the pledges are refunded in such a way that benefits the contributors more than others. Such a refunding policy was proven to motivate all beneficiaries making pledges for payments [77, 78].

Here we formulate the use of assurance contract which imposes the *second* constraint of the DRX market clearing optimization model. Our analysis focuses on practical issues particularly relevant for the DRX, with numerical study given in Section 3.4. It is *not* our purpose to re-examine the theoretical aspects already described elsewhere in the economic literature.

Let us consider three arbitrary DR buyers:  $j$  (e.g., Reco),  $j'$  (e.g., Disco), and  $j''$  (e.g., Transco), who together intend to purchase a common quantity  $x_{i,l}$  at a marginal cost  $c_{i,l}$  from customer  $l$  as a DR seller. As per assurance contract, the payment allocation among these buyers for that quantity must satisfy [77]:

$$P_k^{i,l} \geq \delta_k^{i,l} \cdot (c_{i,l} x_{i,l}) \quad \forall k \in \{j, j', j''\} \quad (3.10)$$

The left hand side of (3.10) represents an actual payment, denoted by  $P_k^{i,l}$ , made by only one buyer for the common DR just *after* the market is cleared. This payment must be at least equal to a threshold amount according to the assurance contract. This amount is referred to as an “obligatory contribution”. It is determined by multiplying the DR revenue  $c_{i,l} x_{i,l}$  of the customer  $l$  by the so-called contribution rate  $\delta_k^{i,l}$ —a fixed parameter specified in the assurance contract.

Without obligatory contributions from buyers, one buyer may pay less than the others, regardless of how much benefit it gains from DR. Some buyers may avoid paying anything at all but at the same time enjoy the benefits of DR. Non-paying beneficiaries are referred to as “free riders”, and they can cause substantial distortions of a market [78]. Consequently, an assurance contract specifying the contribution rate of each buyer in the market is necessary to avoid this free-rider problem, and thus ensure market efficiency.

For a given DR quantity  $x_{i,l}$  to be supplied, the total obligatory contributions  $\sum_k \delta_k^{i,l} \cdot (c_{i,l} x_{i,l})$  must match the customer revenue [77]:

$$\delta_j^{i,l} + \delta_{j'}^{i,l} + \delta_{j''}^{i,l} = 1 \quad (3.11)$$

For this constraint, we can easily deduce that:  $\sum_k P_k^{i,l} \geq c_{i,l} x_{i,l}$ . This means all buyers collectively may have to pay an amount that is greater than the payment made to the customer. In economic theory, this discrepancy is commonly known as “payment excess”, which represents an imbalance between the buyer’s payment and the seller’s revenue. Fig. 3.6 shows that as the quantity  $\mathbf{x}$  deviates from the equilibrium point  $\mathbf{x}^*$  payment excess occurs (as depicted by the area  $(B + C)$ ). There are two common ways to deal with this excess [6]. First, if the excess is small, it may be kept by the DRXO to recover the cost of running the market. Second, if the excess is relatively high, part of it will be *refunded* back to the buyers using certain refunding policies (i.e., proportional to their own contributions). These two payment excess scenarios are also considered part of the assurance contract arrangement [79].

Now, without the loss of generality, we consider only the buyer  $j$ . It buys DR not only from the customer  $l$ , but also many others—each included in a group  $n \in \mathcal{N}_j$  associated with buyer  $j$ . Following the condition in (3.10), the buyer total payment to all these customers must satisfy:

$$P_j^{\text{total}} = \sum_{i,l} P_j^{i,l} \geq \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}_i} u_{i,l}^{j,n} \cdot \delta_j^{i,l} \cdot (c_{i,l} x_{i,l}) \quad (3.12)$$

However  $P_j^{\text{total}} = \sum_{n \in \mathcal{N}_j} p_{j,n} y_{j,n}$ , then we imply:

$$\sum_{n \in \mathcal{N}_j} p_{j,n} y_{j,n} \geq \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}_i} u_{i,l}^{j,n} \cdot \delta_j^{i,l} \cdot (c_{i,l} x_{i,l}) \quad (3.13)$$

A practical issue stemming from this condition is that the buyer  $j$  purchases the DR from a large number of customers. This results in a large number of corresponding parameters  $\delta_j^{i,l}$  being considered in the contract. In this paper, for illustrative purposes, we assume that these parameters are all equal to a common value  $\delta_j$ . This assumption does not affect the comparison between the DRX and partial DR approaches. The assumption implies the following variation on the previous constraint:

$$\sum_{n \in \mathcal{N}_j} p_{j,n} y_{j,n} \geq \delta_j \left[ \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}_i} u_{i,l}^{j,n} \cdot (c_{i,l} x_{i,l}) \right] \quad \forall j \in \mathcal{J} \quad (3.14)$$

For further simplification, we assume that the value of  $\delta_j$  is: 1) commonly  $\delta_R$  for every buyer  $j$  who is a Reco; 2) commonly  $\delta_D$  for every buyer  $j$  who is a Disco; 3)  $\delta_T$  for the Transco only. Following the condition in (3.11), we imply:

$$\delta_R + \delta_T + \delta_D = 1 \quad (3.15)$$

We call the vector  $\delta = [\delta_R \ \delta_T \ \delta_D]$  the “contribution rates” vector, which is a core, pre-determined parameter of the DRX model. Since the value of  $\delta$  is decided by agreement between the buyers via an assurance contract prior to market clearing, it plays the role of being *pledges* mentioned above. Specifically if no buyer pledges to contribute then no DR as a public good will be scheduled. The more amount of pledges is made in the contract, the more DR quantity is to be supplied. Such an impact of the pre-determined parameter  $\delta$  on DRX market clearing outcome will be analysed via numerical study in Section 3.4.

Overall, the developed DRX optimization model has  $x_{i,l}$  and  $y_{j,n}$  as the decision variables, (3.6) as the objective function, (3.9) and (3.14) as the constraints, as well as (3.8) and (3.15) as the supporting calculations.

### 3.4 Numerical example

This section provides a simple case study to demonstrate the applicability of the proposed pool-based market clearing model for DRX. Specifically we aim to examine the following aspects which arise from the above discussion.

1. The advantage of DRX (as a comprehensive approach for scheduling DR) over the existing partial approaches.
2. The fairness across all electricity customer in DR provision.

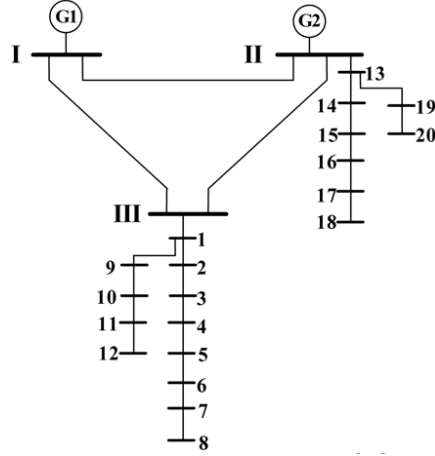


Figure 3.7: The test system

3. The relationship between market clearing prices and purchased quantities.
4. The impact of assurance contract (i.e., contribution rate vector) on DRX market clearing outcome.
5. The truthfulness of DR buyers and sellers when submitting bidding data for market clearing.

### 3.4.1 Test system

Fig. 3.7 given the power system used for this case study. This system is comprehensive in the sense that it includes both transmission and distribution networks which are operated by a Transco and a Disco, respectively. There is also a Reco and an ESCo—each deal with all customers in the power system. For simplicity we assume that each customer represents a single load point connecting with the corresponding distribution feeder, and then there are 20 customers in total. In practice, each load point may include several small customers (i.e., households, small businesses), but by aggregation these customers can be combined into a larger electricity consuming unit suitable for our study here.

Table 3.3: Grouping customers under each DR buyer

Buyer $j$	$\mathcal{N}_j$	Description
Transco	$\{\{1, 2, \dots, 12\}, \{\text{other customers}\}\}$	Each group $n \in \mathcal{N}_{\text{Transco}}$ connects to a trans. load point.
Disco	$\{\{1\}, \{2\}, \dots, \{19\}, \{20\}\}$	Each group $n \in \mathcal{N}_{\text{Disco}}$ connects to a feeder load point.
Reco	$\{\{1, 3, 4, 5, 9, 15, 19\}, \{\text{other customers}\}\}$	Each group $n \in \mathcal{N}_{\text{Reco}}$ is with a single contract type.

Table 3.3 shows the grouping of the customers under each DR buyer for the purpose of DRX market clearing. Here the Transco buys aggregated DR from two customer groups—one includes customers connecting to bus II and the other to bus III of the transmission network. The Disco associates with the same customers but at the distribution level, where these customers are arranged in 20 small groups corresponding to 20 feeder load points. Unlike the Transco and the Disco, the Reco as another DR buyer groups the customers according to the electricity retail contracts offered. That is, customers with the same type of contracts are arranged in one group.

According to the power system structure and the customer grouping, the DRX market clearing system is given by:  $\mathcal{I} = \{\text{ESCO}\}$ —the set of DR sellers;  $\mathcal{L}_{\text{ESCO}} = \{1, 2, \dots, 20\}$ —the set of customer providing DR;  $\mathcal{J} = \{\text{Transco}, \text{Disco}, \text{Reco}\}$ —the set of DR buyers;  $\mathcal{N}_{\text{Transco}} = \{\text{I}, \text{II}\}$ —the set of customer groups associated with the Transco;  $\mathcal{N}_{\text{Disco}} = \{1, 2, 3, 4, \dots, 20\}$ —the set of customer groups associated with the Disco;  $\mathcal{N}_{\text{Reco}} = \{\text{A}, \text{B}\}$ —the set of customer groups associated with the Reco.

### 3.4.2 Assumptions on the supply and demand curves

To clear the DRX market using the above global optimization model, the DRXO collects data representing the demand and supply curves from buyer and sellers. For simplicity, such input data for market clearing is to be assumed here (It will be investigated in Chapter 6 using a local cost/benefit analysis.)

For the ESCo and its customers, we assume a linearly increasing supply curve and corresponding quadratic cost of producing DR, as follows [40, 81]:

$$c_{i,l} = 2a_i x_{i,l} + b_i(1 - \theta_{i,l}) \quad (3.16)$$

$$C_i = \sum_{l \in \mathcal{L}_i} (a_i x_{i,l}^2 + b_i(1 - \theta_{i,l})x_{i,l}) \quad (3.17)$$

where  $i \in \mathcal{I} = \{\text{ESCO}\}$ , and  $l \in \mathcal{L}_i = \{1, 2, \dots, 19, 20\}$ . The coefficient  $\theta_{i,l}$  is called the “customer type” and takes a value between 0 to 1.  $\theta_{i,l}$  represents a customer’s willingness to curtail load to provide DR. As  $\theta_{i,l}$  increases, the cost of DR decreases because the customer is more willing to participate. (Values for this parameter are given in Table 3.4.) Besides  $\theta_{i,l}$ ,  $a_i$  and  $b_i$  are common coefficients applied to all customers,  $a_i = 10\$/\text{MW}^2\text{h}$ ,  $b_i = 120\$/\text{MWh}$ .

The reason behind using (3.16)—(3.17) for modeling the supply curves is, to compare the relative DR scheduling outcomes among various customers based on their own curtailment willingness. In order words, we intends to analyse the impact of  $\theta_{i,l}$  on  $x_{i,l}$  and other relavent market clearing parameters at the individual customer level. This analysis reveals the fairness across all customers in DR provisions.

Table 3.4: Customer types

Cons $l$	$\theta_{i,l}$	Cons $l$	$\theta_{i,l}$	Cons $l$	$\theta_{i,l}$	Cons $l$	$\theta_{i,l}$
1	0.75	6	0.8	11	0.85	16	0.9
2	0.76	7	0.81	12	0.86	17	0.91
3	0.77	8	0.82	13	0.87	18	0.92
4	0.78	9	0.83	14	0.88	19	0.93
5	0.79	10	0.84	15	0.89	20	0.94

For each DR buyer in the market, we assume a linearly decreasing demand curve and corresponding quadratic gross benefit [49, 81]:

$$p_{j,n} = -2\alpha_{j,n}y_{j,n} + \beta_{j,n} \quad (3.18)$$

$$B_j = \sum_{n \in \mathcal{N}_j} (-\alpha_{j,n}y_{j,n}^2 + \beta_{j,n}y_{j,n}) \quad (3.19)$$

where  $j \in \mathcal{J} = \{\text{Reco}, \text{Transco}, \text{Disco}\}$ , and  $n \in \mathcal{N}_j = \mathcal{N}_{\text{Reco}} \parallel \mathcal{N}_{\text{Transco}} \parallel \mathcal{N}_{\text{Disco}}$  (see Table 3.3 for details). The coefficients  $\alpha_{j,n}$  and  $\beta_{j,n}$  are *valuation* coefficients assigned to each customer group  $n$  under buyer  $j$ . These coefficients reflect how much DR provided by the group is “worth” for the buyer in each given time period. For example, during the time of peak demand, it may be costly to maintain network security using conventional means. In stead, the network operator can utilize DR to reduce demand, and thus improve network security, resulting in significant cost savings [82]. In terms of our formalisation, the savings are the operator’s gross benefit as defined in (3.19). Savings can be calculated using a cost/benefit analysis incorporated with a reliability assessment [83].

The Reco, on the other hand, can use DR to cover most financial risk caused by electricity spot price volatility. In economic theory, such a strategy is referred to as a financial hedge, in which the Reco offsets investment (i.e. the demand to be met from spot markets) in order to minimize unwanted exposure to risk. This is done by using DR to reduce the amount of power the Reco needs to buy during periods of high spot market prices. In this strategy the gross benefit derived from DR is equivalent to the benefit from risk reduction which can be calculated using a hedge analysis [84].

Both the reliability assessment and hedge analysis for individual buyers are beyond the scope of this chapter which is focused on demonstrating the feasibility of a DRX. Consequently, some simple data related to this assessment and analysis are employed as input to the DRX model. The input data is contained in the values of coefficients  $\alpha_{j,n}$  and  $\beta_{j,n}$  which are listed in Table 3.5.

Table 3.5: Valuation coefficients

DR buyer $j$	Group $n \in \mathcal{N}_j$	$\alpha_{j,n} (\$/\text{MW}^2\text{h})$	$\beta_{j,n} (\$/\text{MWh})$
Reco	1 to 2	1	50
Transco	1 to 2	1	50
Disco	1 to 20	10	50

### 3.4.3 Modeling of partial DR approaches

To evaluate the performance of a DRX, comparing it with existing partial approaches for scheduling DR is necessary. As were indicated in the previous chapter, these approaches include Reco-based, Transco-based and Disco-based programs. In the following we review such DR scheduling programs from a market clearing perspective:

#### Transco-based model

This class of DR-scheduling schemes is operated by Transcos that are primarily responsible for managing the security of transmission networks [85]. Within a Transco-based scheme, customers provide DR as a resource in the form of load curtailments to balance the active power generation and demand on a given timescale (e.g., hour-ahead), consequently ensuring transmission network security. Examples of the Transco-based scheme can be found in [40, 49, 80, 85, 87, 88].

Traditionally DR has been provided under strict conditions such that the Transco is allowed to curtail loads of any customer (given that these curtailments improve network security) and then compensate these customers with a fixed fee [88]. Many competitive approaches for DR procurement have been proposed during the last twenty years. Competition in supplying DR could be introduced by using either interruptibility contracts between the Transco and customers, or some type of organized market-based scheme [87]. Under contract arrangements, each customer negotiates DR with the Transco on a monthly or yearly basis. Under a market-based scheme, all customers independently offer their own capacity in a spot market on a daily or hourly basis, where the Transco clears these offers based on the benefits for all involved parties (including the Transco itself). The market-clearing approach has been given more attention than the contract approach in recent years. In fact, some power utilities in Australia, the U.S., and Europe have implemented dedicated spot markets for trading DR [88]. These markets could achieve economic efficiency as competitive prices are taken into account in the selection of customers supplying DR.

#### Disco-based model

This category of DR schemes is related to Discos operating a local distribution network consisted of many radial feeders connecting directly with the customer loads. As similar to

the Transco, Discos benefit from DR by using it to enhance distribution network security. Examples of a Disco-based scheme can be found in [80, 86–88].

In this scheme, Discos directly schedule and pay for the load curtailments offered by their customers. The payment calculation is based on both Disco and customer benefits. The latter can be estimated by either surveying customers or using historical data obtained from the same DR program [86].

### **Reco-based model**

The final category focuses on Recos, who provide contracts for selling electricity at given prices to small customers. Examples of Reco-based DR-scheduling scheme can be found in [80, 87–90].

Within this scheme, customers submit offers specifying financial incentives at which they are willing to reduce loads for providing DR. The Reco then clears these offers considering the benefits for customers and the Reco itself [90]. Profit for the customers is a compensation for the load curtailment, while profit for the Reco is a reduction of risk caused by spot price volatility. The curtailment compensation is either change of retail price or an amount of reward that is unrelated to that price. The former is considered to be beyond the scope this paper.

### **Common aspects**

In all above scheduling categories, DR in the form of load curtailment is treated as a market product being negotiated between two involved parties. For example, within a Reco-based scheme, DR from customers are offered to the Reco for mitigating spot price volatility.

Under this operating paradigm, a market clearing approach was developed for each category of DR scheduling [85, 86]. As such, demand for the DR product is matched by its supply. For simplicity we assume that the main objective of all such market clearing approaches is to maximize the total benefit for all participants, as was suggested in [86]. Under this assumption, each approach is equivalent to a special case of the DRX, in which only one buyer pays for DR, while the others are considered free riders who pay nothing at all but gain some DR benefits. Market clearing optimization models for these partial approaches are given in Table 3.6. In each partial model, free riders are removed from the market-clearing process, simply because they do not pay. Their free benefits are, however, still taken into account for the comparison. Additionally, no assurance contract is used in these models, and therefore constraint (3.14) is removed as well.

The aim of using these market clearing models for describing the partial DR approaches is, to provide a “fair” comparison with the proposed DRX approach. Specifically with the same data inputs and similar optimization objectives, the advantage of each approach over others can be easily observed. In reality, modeling the partial approaches may entail



Table 3.6: Partial DR models

Models	$\mathcal{I}^{\text{partial}}$	$\mathcal{J}^{\text{partial}}$	Equations
Reco-based	{ESCo}	{Reco}	(3.6)—(3.9), (3.16)—(3.19)
Transco-based	{ESCo}	{Transco}	(3.6)—(3.9), (3.16)—(3.19)
Disco-based	{ESCo}	{Disco}	(3.6)—(3.9), (3.16)—(3.19)

further practical considerations that are, for simplicity, omitted here. We believe that lack of such considerations will not affect the comparative outcome.

#### 3.4.4 Analysis of the main results

All market clearing optimization models, including DRX and partial, are simulated using the non-linear programming solver called General Algebraic Modeling System (GAMS), with the same data inputs applied. The simulation here is assumed to be within a single-hour period. The results are given in Tables 3.7 and 3.8. Table 3.7 shows the net benefits (that is gross benefit less the cost) for each individual player and for all players together (total market benefit). Table 3.7 presents total DR quantity, payment made by each buyer, and the total revenue of all customers combined. In the simulation, the contribution rates vector  $[\delta_R \ \delta_T \ \delta_D]$  of the DRX model is set at approximately  $[\frac{1}{3} \ \frac{1}{3} \ \frac{1}{3}]$ .

Table 3.7: Comparative net benefit (\$)

Model	Total market benefit	Reco benefit	Transco benefit	Disco benefit	Customers benefit
Reco based	1521.5	121.3	641.3	621.6	137.3
Transco based	1562.3	644.5	126.2	649.1	142.5
Disco based	1565.3	645.2	661.7	129.2	129.2
DRX	<b>2124.1</b>	544.8	520.6	529.4	<b>529.3</b>

Table 3.8: Comparative DR quantities (MW) and payments(\$)

Model	DR quantity	Reco payment	Transco payment	Disco payment	Cons revenue
Reco based	15.2	516.4	0	0	516.4
Transco based	15.8	0	539.2	0	539.2
Disco based	15.7	0	0	526.5	526.5
DRX	<b>32.2</b>	517.6	566.1	548.7	<b>1632.4</b>

As can be seen from the simulation output, results of the DRX are significantly better than those of partial DR approaches. The total market benefit is improved by more than

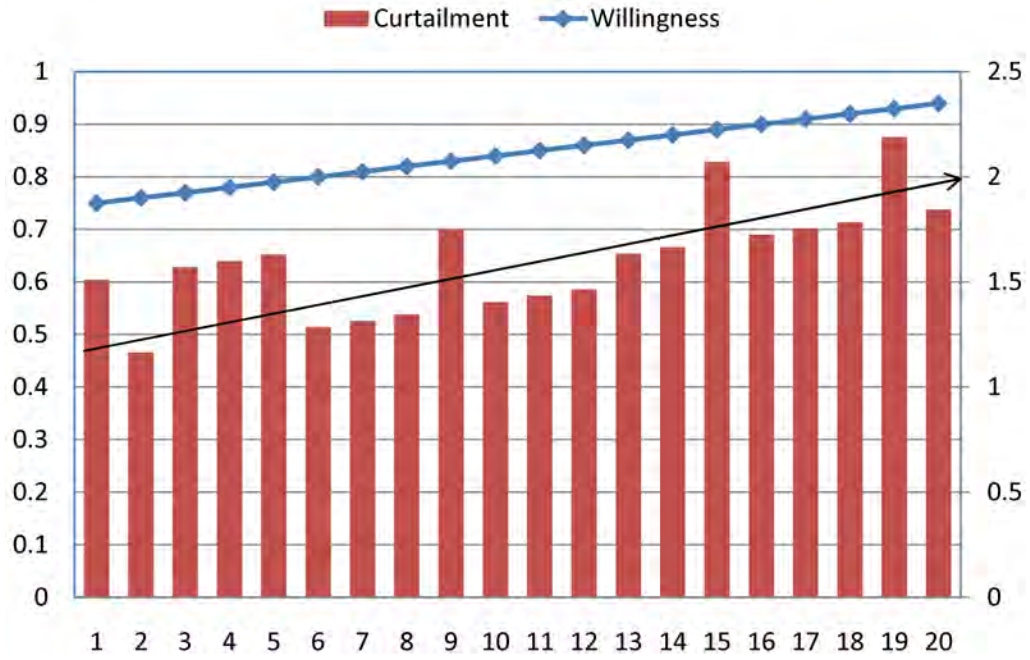


Figure 3.8: Load curtailment (in MWh on the right axis) versus customer willingness (on left axis with no unit). Note: the horizontal axis represents customer index

35%. At the same time, the customer benefit is improved by approximately 300%; total DR quantity, increased by more than 100%; and the corresponding customer revenue increased by nearly 220%.

In partial approaches, there are some players who do not pay for DR. However, their free benefits are only about 15% (Reco), 20% (Transco), and 18% (Disco) higher than would be the case in the DRX. This is because when all players contribute, both the total payment and the resultant DR quantity are improved. Consequently, the gross benefit for each player significantly increases, which compensates for the player's payment.

With these results, we can argue that a DRX is more efficient than partial approaches. This argument is consistent with the microeconomic theory. As indicated in [75, p. 362], “private provision leads to an inefficient level of a desirable public good”. In the context of DR scheduling, a private provision refers to partial approaches since DR, as a public good, is sold to only one buyer. The term “inefficient” here means that the total market benefit cannot reach the global maximum value due to insufficient good being provided. The above results support the claim that partial approaches lead to inefficient DR markets.

Fig. 3.8 examines the relationship between the individual curtailment amount ( $x_{i,l}$ ) and the curtailment willingness ( $\theta_{i,l}$ ) of various customers. Here  $x_{i,l}$  generally increases following the increasing value of  $\theta_{i,l}$ , which implies that customers would curtail more load for supplying DR as they are more willing to do so. However, there are certain customers (i.e., 3, 4, 5) having relatively low willingness but curtailing more load than some others.

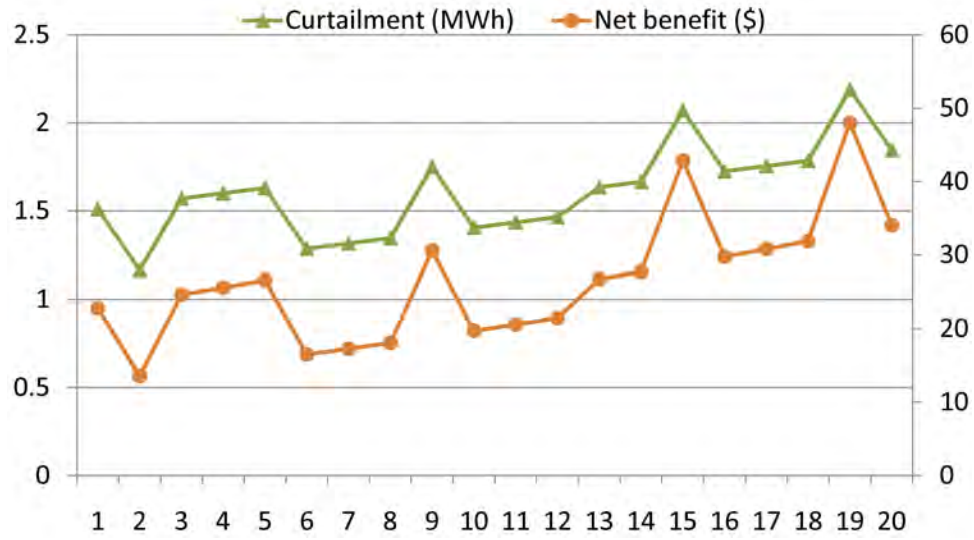


Figure 3.9: Net benefit (on the right axis) versus load curtailment (on the left axis). Here the horizontal axis represents customer index

This result can be explained by the effect of DRX market clearing, where the curtailment amount (or rather DR supply) is *jointly* decided by the customers and the DR buyers. In this situation, if the DRs from some customers are more valuable for the buyers than those from other customers, the former would be purchased at higher quantities and, of course, higher prices than the latter regardless of the curtailment willingness of each customer. For example, the Transco will be likely to buy more DR quantities of those customers at “critical” locations of the transmission network (that is, the locations significantly affecting the network security) than DR quantities of other customers. These results demonstrate the advantage of using market clearing for scheduling DR, where the outcome is given by an optimal balance of the curtailment willingness (or DR supply capability of the customers) and the buyer demand.

Fig. 3.9 shows the net benefit for each individual customer according to their DR quantities supplied. Since such benefits are the difference between DR payments and DR provision costs, they give the “ultimate” incentives for load curtailments. As can be seen from the graph, there is a near-perfect correlation between the curtailments and the net benefits across all customers, that is, those customers curtailing more load than others enjoy higher monetary gains. What is surprising, this correlation is independent of other market clearing parameters such as the curtailment willingness of customers ( $\theta_{i,l}$ ) and the buyer demand for DR. This result demonstrates the very fairness across all types of customers when supplying DR, that is, regardless of which condition the power system is in (normal or contingencies, or with electricity market volatility) and regardless of how much the customers are willing to curtail loads, the more they do the more they gain.

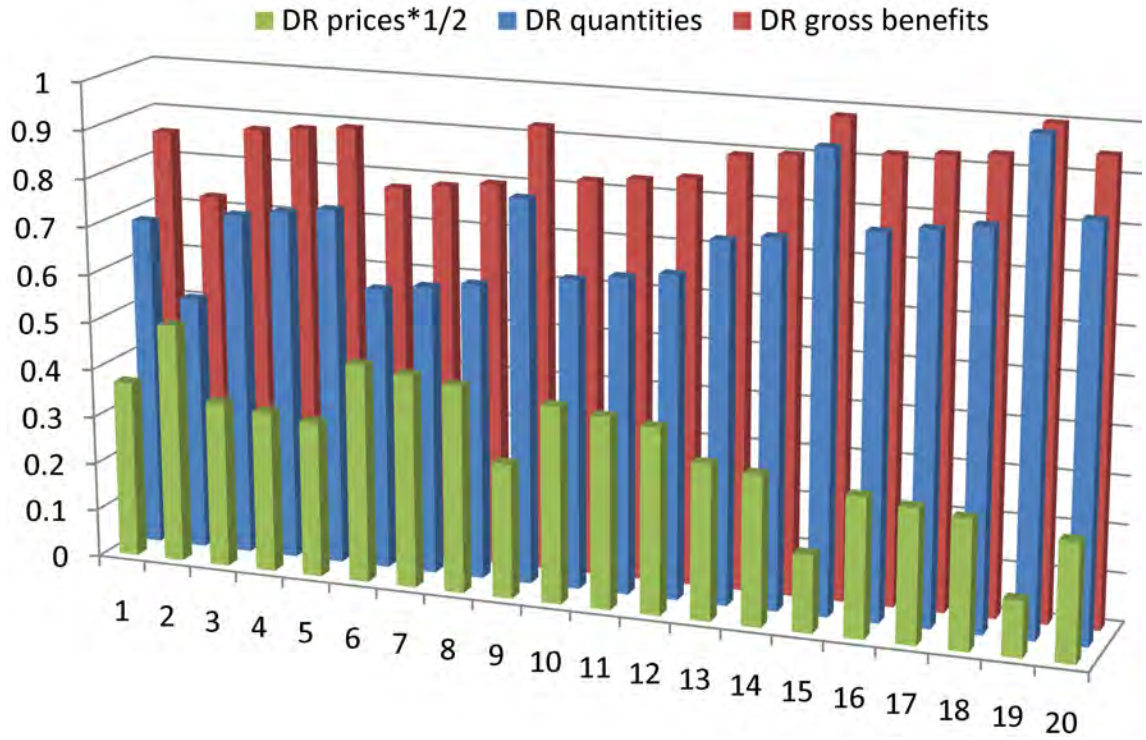


Figure 3.10: The relationship of DR market clearing prices, quantities purchased, gross benefit for the Disco (the results here are normalized by the corresponding peak values.)

In addition to the customers as DR providers, here we examine the market clearing outcome from a DR buyer perspective. For illustrative purposes, we choose the Disco as it deals with all customers at the individual level and consequently gives more diversified results than other buyers including the Reco and the Transco, who deals with only a limited number of aggregated customers (i.e., 2 as of Table 3.3). Fig. 3.10 presents the correlation between DR quantities and their market clearing prices paid by the Disco. It is observed that the former is *inversely* proportional to the latter, which can be explained by the law of demand in microeconomics. That is, people tend to buy more of the cheaper products and avoid purchasing the expensive unless necessary.

Fig. 3.10 also gives the relationship between the purchased quantities and the gross benefit derived from each quantity. As can be seen, those DRs giving more benefits than other DRs will be purchased by the Disco at higher quantities. In other words, higher DR quantities must bring out more gross benefits, otherwise they would not be cleared in the market. Such an argument can be referred as “rationality” in DRX market clearing.

### 3.4.5 Discussion of other results

Further simulations are performed to examine the impact of the contribution rates vector  $[\delta_R \delta_T \delta_D]$  on the DRX market outcome. As can be seen in Table 3.9, the total market net

benefit deviates from the global optimum as  $[\delta_R \ \delta_T \ \delta_D]$  deviates from  $[\frac{1}{3} \ \frac{1}{3} \ \frac{1}{3}]$ . This is due to the *inconsistencies* of payment contributions among buyers with respect to the benefits they get from trading DR. For example, as  $[\delta_R \ \delta_T \ \delta_D]$  is  $[\frac{1}{4} \ \frac{1}{2} \ \frac{1}{4}]$ , both the Reco and Disco benefit more but contribute less, while the Transco benefits less but has to contribute more. Although this unfair situation is not a serious free-rider problem, it can still distort market efficiency [75]. An additional consequence is that an excess of payment (554.5\$) occurs, meaning the buyers together have to pay more than the customers receive.

Table 3.9: The impact of contribution rates vector on DRX outcome

$(\delta_R, \delta_T, \delta_D)$	Total market benefit	Reco benefit	Transco benefit	Disco benefit	Payment excess
$(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$	2124.1	544.8	520.6	529.4	$\approx 0$
$(\frac{1}{4}, \frac{1}{2}, \frac{1}{4})$	2042.1	391.5	340.1	378.5	554.5

Although this contributions issue is not a major problem for DRX market-clearing, it demands that each DR buyer has to pay attention when signing onto the assurance contract. There is a requirement for choosing appropriate values for contribution rates, which should be proportional to the predicted benefits in the future DR trading [77].

The contributions issue also leads to an interesting observation that each buyer has a reasonable incentive to *truthfully* declare their own benefits when negotiating contracts with other buyers. If a buyer attempts to game the market by “lying” about its benefit, the  $[\delta_R \ \delta_T \ \delta_D]$  that is determined using this false benefit will unfortunately become *inconsistent* (i.e., deviating from the optimal value). As a consequence, the actual benefit the buyer eventually receives after the DRX is cleared will be lower than the benefit the buyer could receive if its claim has been more “honest”. Seeing Table 3.9 as an example, where  $[\frac{1}{3} \ \frac{1}{3} \ \frac{1}{3}]$  corresponds to “no buyer lied”, and  $[\frac{1}{4} \ \frac{1}{2} \ \frac{1}{4}]$  corresponds to “both the Reco and Disco lied but the Transco did not”.

In this example, the Transco who did not lie must also suffer from a benefit reduction caused by “dishonest” buyers. This unfair situation can be resolved introducing a mechanism to refund the payment excess as an additional incentive for buyers not to lie. As indicated in Section 1.2.4, refunding the payment excess back to buyers is proportional to their own contributions. For example, in Table 3.9, the Transco, Reco, and Disco, who contribute at rates  $\frac{1}{2}$ ,  $\frac{1}{4}$ , and  $\frac{1}{4}$ , will receive 277.4\$, 138.7\$, and 138.7\$, respectively (assuming that the payment excess 554.5\$ is fully refunded). Consequently, the total benefit for the Transco will be 617.5\$ which is higher than the total benefits to the lying Reco and Disco (i.e. 530.2\$ and 517.2\$). In comparison to the  $[\frac{1}{3} \ \frac{1}{3} \ \frac{1}{3}]$  case, the Transco is rewarded while the lying buyers are penalized.

This result is also consistent with microeconomic theory. As shown in [79], a refunding mechanism under the assurance contract motivates any buyer to play a “dominant

*strategy*”, in which regardless of how much other buyers contribute to the public good, the buyer is better off contributing more based on its own true benefit. Such a strategy rewards the buyer with not only a better refund, but also a higher net benefit due to an improvement in the overall market efficiency. If every buyer plays the dominant strategy the market will reach an optimally efficient level with appropriate values for contribution rates (i.e.,  $[\frac{1}{3} \ \frac{1}{3} \ \frac{1}{3}]$  in the above example). Playing the dominant strategies, each buyer will furthermore submit DR bids reflecting true benefits [79]. This, in turn, satisfies the marginal assumption made in Section 1.2.3.

On the other side of the DRX market, electricity customers, as the DR suppliers, have even more incentive to offer DR at marginal rates that reflect true costs. If a supplier attempts to raise the offering price above the marginal rate, it might simply lose the opportunity to sell DR to other suppliers who offer a cheaper price. Under a DRX market with *several million* DR suppliers (electricity customers) no one can hold significant “market power”, so the loss of a DR sales opportunity from one supplier to another due to price competition is likely to happen [75]. Consequently, any supplier is better off offering the DR at a minimal price (that is equal to the marginal rate [75]) to compete well with the other suppliers in the DRX market. If every supplier offers the marginal rate, the market will achieve near-perfect competition in DR supply.

The above observations are mainly based on the general microeconomic theory. The issues related to individual buyer contributions and true-benefit gaming in the particular context of a DRX market obviously need further investigation. In our opinion, the proposed DRX market-clearing scheme under an assurance contract provides a good starting point as it offers clear advantages compared with conventional DR approaches.

A DRX market under the assurance contract can be cleared on an hourly basis. During each hour, buyers receiving a greater benefit contribute more than other buyers, and buyers receiving no benefit are not required to contribute. This hourly arrangement is included in the assurance contract. Note that the contributions among buyers in different hours of the day can differ, depending on their own time-varying benefits. Furthermore, there may exist some off-peak hours when no player benefits from DR. In these hours, no payment is made, and thus no DR is supplied. Such special cases, however, still fall well within the assurance contract arrangement.

### 3.5 Summary

This chapter developed a pool-based market clearing model for DRX in the restructured power system. Here the DRXO collects bids and offers from DR buyers and sellers, respectively. It then clears the market by maximizing the total market benefit for all participants. The theory behind the pool-based DRX is based on a well-known demand-supply model

incorporated with an assurance contract used for solving the free-riding problems associated with public good contributions. Most importantly, such a theory brings together DR buyers (i.e., Transco, Recos, Discos, each with their own reasons to demand some DR from time to time) and sellers (i.e., ESCos on behalf of electricity customers) under a common DRX umbrella.

The DRX market clearing model has an additional advantage in that it rewards customers better by allowing them to deal with multiple buyers in a competitive way. This reward and competition based model can motivate customers to participate in DR programs more actively than in the past.

Numerical simulations have been performed to examine the “core” properties of a pool-based DRX. It was observed that the proposed approach is significantly better than the conventional partial approaches, in the sense that it increases the total market benefit for all participants. In addition, many critical aspects of the DRX were shown to be consistent with microeconomic theory. These are fairness across all customers as DR providers, price-quantity relationship, and truthfulness in submitting demand and supply data for market clearing.

## Chapter 4

# Agent-based Market Clearing

### 4.1 Overview

This chapter presents the design and evaluation of an agent-based market clearing mechanism for DRX, in which each market participant (i.e., buyers and sellers) is represented by an economic agent behaving in a self-interested manner. This means that the agent always attempts to maximize its local benefit based on the available information about actions taken by other agents participating in the same DRX market. The proposed market clearing mechanism uses Walrasian auctions, where the agents update their locally optimal bids for DR quantities in response to prices adjusted by the DRXO. This auction is repeated iteratively until market equilibrium is obtained at the point where the market outcome is Pareto efficient from a global perspective. Both analytical proof and numerical simulation are provided to support key arguments.

Convex optimization theory is used as the mathematical background to formulate the market clearing problem with the aim of maximizing total market benefit for all participating agents. This problem is then converted into a set of equivalent conditions using Karush–Kuhn–Tucker (KKT) theorems. Such conditions which constitute a market equilibrium point are solved iteratively using Walrasian auction design.

This chapter is structured as following. Section 4.2 describes the concept of economic agent and its implications for a DRX. Section 4.3 formulates the market clearing problem from an agent-based perspective. With this formulation Section 4.4 designs the Walrasian auction mechanism, which will then be theoretically evaluated in terms of optimality and convergence in Section 4.5. Numerical studies of the proposed mechanism are given in 4.6 and concluding remarks due in Section 4.7.



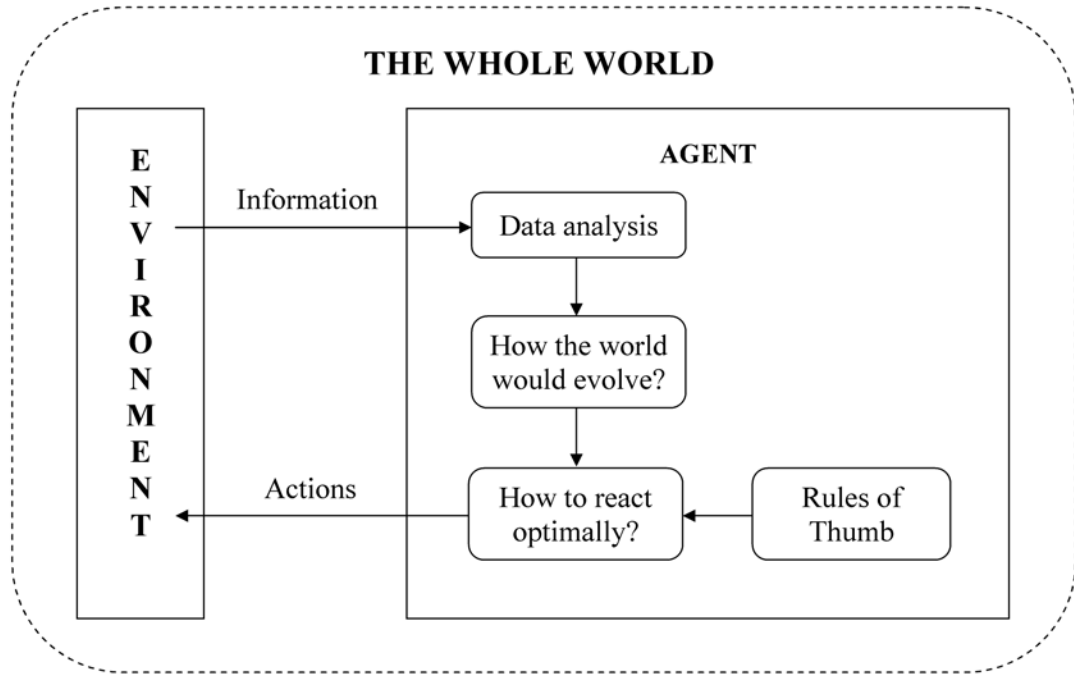


Figure 4.1: Agent with a local view into the world

## 4.2 Agent-based market concepts

### 4.2.1 Economic agents

Agent is an important concept in different fields such as economics, engineering, computer science, and social science. Generally, it refers to an individual entity capable of making decisions based on a set of rules and the available information about environment where the agent is involved in [91]. The term “rule” here is formally given by conditional statements (i.e., if-then-else) with input data leading to output decisions.

The agent concept is illustrated by Fig. 4.1, where each agent is assumed to have only a local view of the world where they are in. Such a localization means that the agent cannot know exactly the actual *state* of the entire world, regardless of how much information it can gather from the outside environment. Such information includes decisions made by other agents and the coordination between them. As shown in Fig. 4.1, first the agent tries to analyse the collected information to see how the world would look like. Then the agent determines which optimal decisions to be made in accordance with some pre-determined rules of thumb. These decisions lead to some actions taken by the agent when interacting with the environment, for instance, collaborating with other agents for a mutual benefit. Table 4.1 gives different types of agents to be discussed here.

Human world is a typical example of agent-based environment where each person in it is considered an agent. Here people could either make individual decisions for themselves

Table 4.1: Types of agents

Types	Characteristics
Human agents	Local view, self interest, autonomous
Intelligent agents	Local view, computerised, autonomous
Economic agents	Local view, computerised, self interest

or joint decisions with other people. The former, for example, can relate to the tomorrow's electricity consumption, while the latter may be an election where people together vote for president. These decisions generally rely on how people understand the surrounding issues, for instance, how the electricity price would be evolving for tomorrow, or whether someone deserves the president position. Such understandings are often subjective as varying from people to people depending on their own observations of the issues. In this regard, different observations can lead to biased decisions among people. These examples show that each person as an agent only have a local view of the world [3, 8].

In many systems working in real time (i.e., power systems), operational decisions have to be made fast, minutes rather than hours. This task which may be beyond human capabilities consequently entails using computers as a decision-support tool. This is the case during emergency and abnormal power system conditions, where the human operator has to deal with a very large amount of data and apply most appropriate remedial actions [92]. But due to emotional and psychological stress, the operator may not be able to make correct decisions for such conditions. Hence, there is a need for computer-aided tools to improve the computational speed and assist the operator in decision making. Such tools are referred to as software agents. If these softwares are capable of undertaking some autonomous tasks without human support, they are called intelligent agents. On the other hand, those softwares doing market negotiation on behalf of people are “economic agents” which are the focus of this chapter [75].

The need for economic agents is fairly similar to the case of intelligent agents, which is to supply and/or acquire resources instantly from relevant markets. This entails online trading tasks that, again, could be beyond the human capabilities and thus are performed automatically by computer softwares as economic agents. This is the case in an electricity wholesale market, where electricity demand and supply—generation and load—must be balanced on a second-by-second basis so as to maintain system security [6]. To deal with this trading issue, each Genco participating in the market employs a dedicated software agent that can automatically offer power supply following the time-varying demand.

An important characteristic of economic agents is that they commonly behave in a “self-interested” manner as inheriting from human. Specifically, the agents always attempts to maximize their own benefits (that is, in fact, the benefits for those people participating in

the market via agents), taking into account the available information about actions taken by other agents. For example, the objective of a Genco when dealing with the electricity market is to optimize its trading profit considering both market prices and strategies of neighboring Gencos [93].

This chapter utilizes the concept of economic agent to develop a DRX in which DR is considered a market product traded between two groups of participating agents, namely buyers and sellers. The former, on behalf of the corresponding electricity utility companies including Transcos, Discos and Recos, purchases DR quantities at optimal market prices. Sellers, on behalf of ESCos and their electricity customers, supply DR as a source of financial income. From a practical perspective, these buying and selling agents are represented by dedicated computer programs involving online market transactions.

Since DR as virtual resource is separated conceptually from electricity, an economic agent for negotiating DR can be considered to be separated from the existing agents for trading electricity in a wholesale market mentioned above. In fact, they are very different business entities—the former maximizes benefits derived from DR resources (supplied by small customers), while the latter deals with bilateral trades of electricity (produced by Gencos) under network security constraints. Practically, these agents are represented by different computer softwares having different business functionalities within a given power company (Gencos, Transcos, Discos, Recos) [68]. Nevertheless, these softwares could be integrated within a “joint” economic agent for the purpose of co-optimizing the company’s total profit derived from providing all relevant resources including DR and electricity.

As a complement of pooling given in previous chapter, agents provide a new perspective for operating DRX since they rely on decision making at the individual (buyer and seller) levels, rather than at an aggregated level (i.e., a pool) where all DR resources are valued and scheduled together. Generally, this agent-based perspective has an advantage of being able to deal with a complex scheduling problem by broking it into a number of smaller problems—each is to be solved locally by a self-interested agent via its profit optimization. Such a *decentralized* approach can reduce the computational cost associated with resource scheduling, and thus enhance the overall system scalability in which the system, without losing its performance, is capable of handling a growing number of agents and an increasing amount of resource to be scheduled [94]. These decentralized advantages of using economic agents over a centralized pool will be discussed further in the following subsection.

#### **4.2.2 Agent-based market clearing mechanisms**

As agents operates locally for their own profits, there is a need for a scheduling mechanism that coordinates all agents towards achieving a global optimal outcome. In the case of a market, such a mechanism is in the form of market clearing which balances the demand

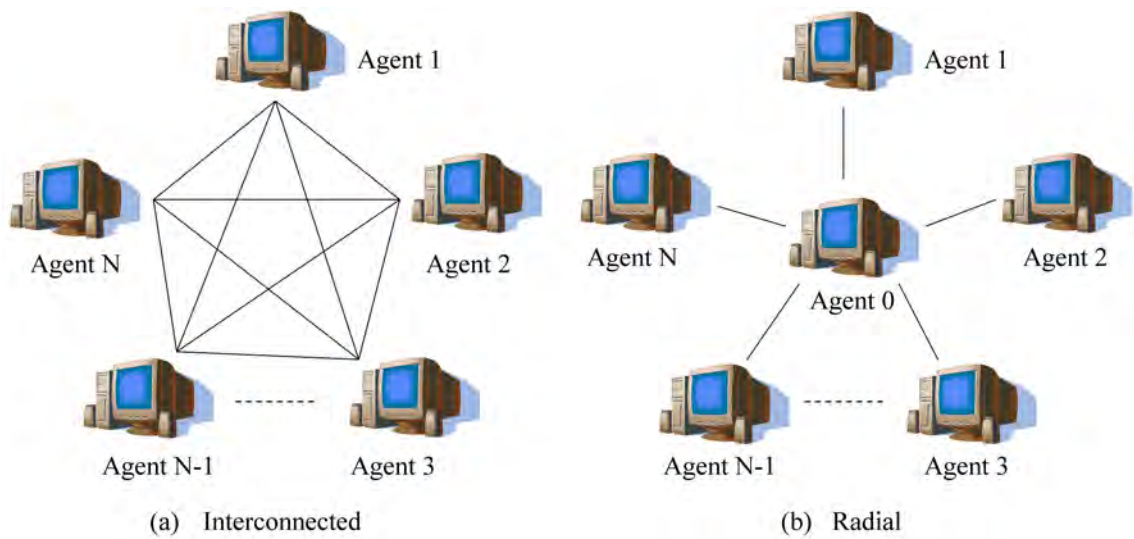


Figure 4.2: Structures of an agent-based market clearing system. Here the lines represent links

of buyers and the supply from sellers [80], with the fundamental aim of constraining each of these self-interested agents in such a way that ensures optimal global market efficiency, while also enabling agents to maximize their local profits [95].

The agent-based market clearing mechanism is illustrated by Fig. 4.2, where there are two main structures of the system, namely interconnected and radial [94]. The former refers to the case where [communication] links are established directly between every two agents without the involvement of a third party. An electrical power transmission network is a good example of interconnected system, where each node is viewed as an agent [96] and the electricity is delivered from one node to another where loads are connected with. In terms of market clearing, interconnected mechanism implies that trades are made independently between every two market agents (a buyer and a seller), such that they arrange by themselves both optimal product quantity and price without any third party intervention, for instance, by the market operator. Such a market arrangement is also called *bilateral* transactions.

By contrast, links in a radial structure must go through a central node that is sometimes given by an agent (i.e., Agent 0 in Fig. 4.2-b). Power distribution network gives a good example of such structures, in which electricity is delivered from a substation to every individual load through a common feeder. In case of a market, radial structure implicates that all buying and selling agents have to send their demand and supply data to a central office designated as the market operator. This entity then sends the updated information back to the corresponding agents, to coordinate them in performing their *local* profit optimization with respect to the current market status. This type of market coordination is sometimes called *multilateral* transactions which are the focus of this chapter.

Although both agent-based multilateral transactions and a pool-based model (given in previous chapter) are commonly coordinated by a market operator, they are different to such an extent that the former considers actions of self-interested agents with the view of assessing their local effects on market outcome as a whole, while the latter tries to aggregate all demand and supply data from market participants (who may or may not employ agents to deal with the trades), for the purpose of centralized profit optimization over the pool. In order to explain the advantages of using agent-based multilateral transactions for market clearing, first we discuss specific issues associated with a pool-based model with a particular focus on the DRX.

### **Limitations of pool-based market clearing**

In a pool-based DRX market, sellers and buyers are required to submit supply offers and demand bids reflecting their true marginal costs and benefits derived from DR. Using this collected information, the DRXO centrally maximizes the total market benefit under several economic constraints such as the demand–supply balance, and the contribution of each buyer for DR as a public good. This pool-based model, following a standard market design, is a formalization of the concept DRX. Unfortunately there are *two* major technical concerns about pool-based market clearing, given as follows.

First, market clearing requires buyers to submit their demand bidding curves independently from electricity market conditions. It is not sufficiently clear how this can be done. We pointed out that the demand curves can be derived using a cost and benefit analysis of DR. However, taking into account that both DR costs and benefits always *depend* on electricity market conditions (i.e., generation dispatch, loading level) it will be difficult to derive a separate DR demand curve.

Second, the core parameter of a pool-based DRX model is contribution rates that reflect the contribution allocation among different buyers who jointly use a common DR. It is not clear how this parameter can be predetermined. We pointed out that the contribution rate assigned to each buyer must be proportional to the predicted benefit that the buyer will gain from future DR trading. This, however, raises concerns about benefit prediction. As power systems are always subject to uncertain factors such as the network instability and market volatility, predicting future DR benefits that heavily depend on these factors is not easy. Without an accurate benefit prediction, the calculated contribution rates may become inappropriate, making the market clearing suboptimal [95].

### **Advantages of agent-based market clearing**

In general, it is difficult to determine which market clearing mechanism between agent-based and pool-based is completely better. Each mechanism here has their own advantages and limitations (see Table 4.2). The advantages of a pool-based model rely solely on its

centralized evaluation where all DR resources are aggregated and valued simultaneously by a common entity—the DRXO, in the effort of making a fair resource allocation across all market agents. On the other hand, one of the major advantages of using an agent-based mechanism is to deal with the above mentioned limitations of the pool-based DRX model.

Table 4.2: Pool-based versus agent-based market clearing models

	Pool-based DRX	Agent-based DRX
Advantages	Resource aggregation, and centralized evaluation.	Reliable and flexible with time-varying system conditions
Limitations	Separate demand curves, core parameters selection.	Untrusted agents

First, since the agent-based market clearing relies mainly on local profit optimizations by self-interested agents, it does not require the agents to submit separate supply and demand curves reflecting their own DR-related costs and benefits. This implies that all DR buying agents including Transcos, Discos, and Recos can incorporate relevant electricity market conditions (such as generation scheduling, network loading level) within their own optimization problem. Such an inclusion ultimately results in a more realistic DRX market clearing, where all necessary information associated with a DRX is considered locally by the corresponding agents and is coordinated by the DRXO. Then the global optimal benefit for all agents together, if it can be obtained, would be a reliable market outcome.

Second, the agent-based model does not include such optimization parameters as “contribution rates” that must be pre-determined from predicted benefits associated with future DR trading. This exclusion minimizes the risk of not predicting such future benefits accurately due to uncertainties in the power system. In other words, the agent-based DRX model is more *flexible* than the pool-based one, as it can adapt to a range of time-varying system conditions. This flexibility generally is the common advantage of any decentralized scheme over the centralized one, from both economic and technical viewpoints [97].

However, both an agent-based DRX and other decentralized schemes can have a common drawback associated with agent’s manipulation when trading in the market. Specifically some “dominant” agents (that are the agents holding a large share of the total market outcome) may take advantage of their local profit optimizations to drive the market in such a way that benefits the agents more than others. For instance, during the 2002 California electricity market crisis, Enron as the major Genco manipulated the market by raising the optimal bidding prices above the competitive level, consequently causing serious market distortions. This example suggested that each agent in a decentralized market cannot be entirely trusted. Therefore, incentive mechanisms for the agents not to manipulate the market should be designed and embedded within a common market clearing framework

(i.e., DRX). This type of mechanism is central to agent-based DRX development given in the following sections.

### 4.3 Formulation of the market clearing problem

This section formulates the DRX market clearing problem serving as a technical *ground* for subsequent agent-based mechanism design and analysis. Firstly, the notion of Pareto efficiency is introduced as an analytically optimal outcome to be achieved by a DRX market as a whole. Such an outcome is then converted into a set of equations which constitute a market equilibrium point and can be solved using practical algorithms.

#### 4.3.1 Pareto efficiency

Pareto efficiency, sometimes called Pareto optimality, is an important concept in welfare economics with applications in engineering (for instance, resource scheduling problems) and computer science (i.e., file sharing tasks). By definition, scheduling a resource such as DR, for a number of agents, is Pareto efficient if no change from this schedule can increase benefit for one agent without reducing benefits for some other agents [75]. This apparently simple outcome plays a central role in the development of the mainstream microeconomic theory to date.

Pareto efficiency has significant implications for real-world markets. It guarantees that the market outcome associated with product scheduling cannot be improved further such that no agent would be disadvantaged from the revised schedule. As there is no further improvement across all market agents, the Pareto schedule is said to be globally optimal. This implication explains the reason why economic optimizations often rely on the Pareto efficient concept.

This important concept is illustrated by Fig. 4.3 where, for simplicity, there are only two agents—a buyer and a seller—who trade a product (i.e., DR) in the market. Trading benefits for the agents is given by  $U_1$  and  $U_2$  which vary according to the trading outcome. Following microeconomic theory, values of  $U_1$  and  $U_2$  are bounded within a *feasible region*,  $\mathbf{R}$ , defined by two axes and the bold curve having a concave form in general [75]. These boundaries could be explained by certain technical and economic factors associated with the resource production and scheduling. As can be seen from the graph, Pareto efficient outcome is obtained at the point P where the boundary curve “just touches” its tangent line  $U_1 + U_2 = b$  (i.e., the middle line in Fig. 4.3). If the pair  $(U_1, U_2)$  moves away from this critical point but still within the feasible region ( $\mathbf{R}$ ), either  $U_1$  or  $U_2$  will be reduced. This property which can be easily proven by geometry demonstrates the notion of Pareto efficiency given above.

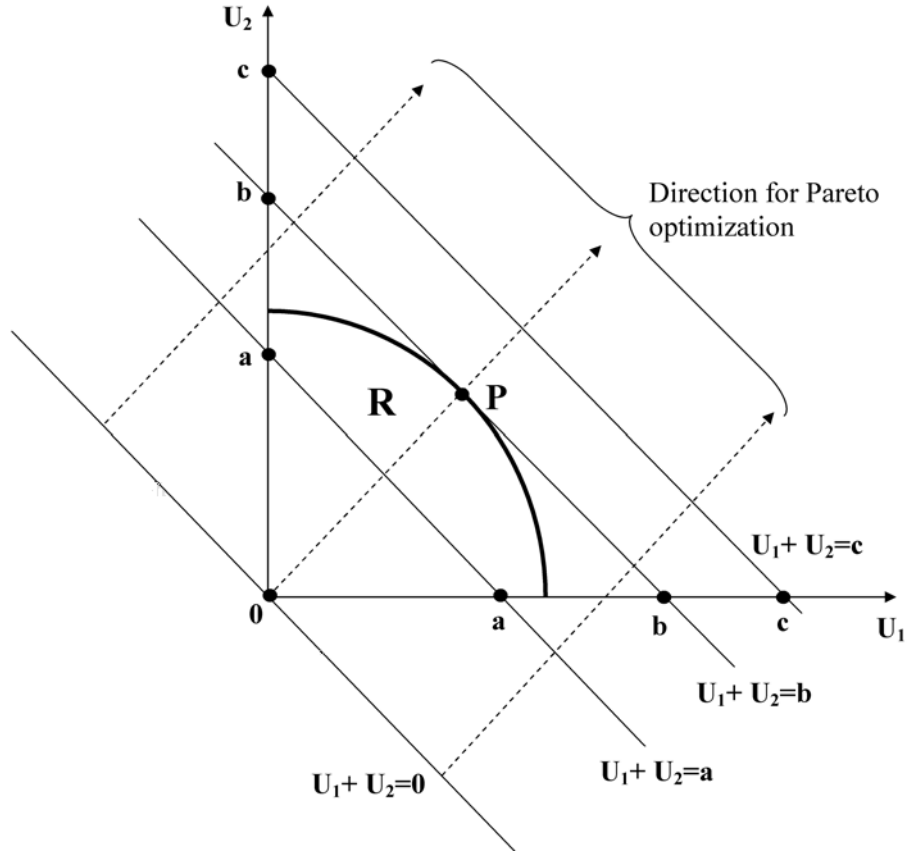


Figure 4.3: Pareto efficiency for a two-agent market

Although Pareto efficient schedule has been well-understood, finding it from a large population of available alternatives, for instance, over the feasible region  $\mathbf{R}$ , is a challenging task. In fact, it is impractical to use the graphical representation given by Fig. 4.3 to identify the Pareto point, because the boundary curve cannot be determined accurately by the market operator due to lack of benefit data that must be collected from all local agents [5]. Additionally in a market with multiple agents (i.e., more than 3) to be represented in a multi-dimensional Euclidean space, finding Pareto efficient point using graphical tools is impossible. Thus, algebraic methods based on symbolic manipulations must be applied.

To derive an algebraic approach for solving the Pareto scheduling problem, we consider again the graph in Fig. 4.3. Supposed that we shift a line [originally given by  $U_1 + U_2 = 0$ ] as far as possible from left to right until it “just touches” the boundary curve at only one point, this point will be  $P$  which represents Pareto efficiency and is given by  $U_1 + U_2 = b$ . If we continue shifting, all corresponding values of  $U_1$  and  $U_2$  [on the line] will go beyond the feasible region  $\mathbf{R}$  and consequently are not accepted. In order words,  $b$  is the maximum horizontal (or vertical) distance for the line to be shifted from the origin  $0$ , within the region  $\mathbf{R}$ . This observation results in the following optimization that algebraically represents the process of finding Pareto efficient point.



$$\max (U_1 + U_2), \quad \text{subject to } U_1, U_2 \in \mathbf{R} \quad (4.1)$$

This statement can be extended to the generic case with an economic system comprised of  $K$  agents, by using a similar illustration with Fig. 4.3.

$$\max \sum_{k=1}^K U_k \quad \text{subject to } U_k \in \mathbf{R} \quad \forall k \quad (4.2)$$

Now we determine how the problem (4.2) can be applied to the particular context of a DRX market comprised of multiple buying agents (i.e., Transcos, Discos, Recos) and selling agents (EScos on behalf of electricity customers). Here we recall all mathematical notations introduced in previous chapter. For each buyer  $j \in \mathcal{J}$ —the set of all buyers in the market, its trading net benefit ( $U_j$ ) is given by the difference between a gross benefit ( $B_j$ ) derived from using a DR and the payment  $P_j$  for this DR. In the case of a seller  $i \in \mathcal{I}$ —the set of all sellers in the market, its trading net benefit ( $U_i$ ) is represented by a difference between the received DR payment ( $P_i$ ) and the actual cost ( $C_i$ ) of producing DR by curtailing some of the electric loads. With these net benefits of buying and selling agents, the first part of (4.2) can be re-written as follows:

$$\max \left\{ \sum_{j \in \mathcal{J}} (B_j - P_j) + \sum_{i \in \mathcal{I}} (P_i - C_i) \right\} \quad (4.3)$$

By assuming that all payments collected from the buyers are given to the sellers [5,8,9], we have  $\sum_j P_j = \sum_i P_i$ . Then (4.3) becomes

$$\max \left\{ \sum_{j \in \mathcal{J}} B_j - \sum_{i \in \mathcal{I}} C_i \right\} \quad (4.4)$$

Equation (4.4) states that a DR schedule is Pareto efficient if the total market “surplus” derived from this schedule for all agents together is maximal. This surplus is measured as the difference between total gross benefit ( $\sum_j B_j$ ) for DR buyers and total cost ( $\sum_i C_i$ ) of producing DR by sellers. The surplus optimization here is consistent with our demand–supply analysis in previous chapter. It is considered the objective of an agent–based market clearing mechanism.

The constraint of this optimization problem has been illustrated by the feasible region  $\mathbf{R}$  in Fig. 4.3. In a DRX market, it is the matching between DR quantities demanded by buyers and those supplied by sellers. This constraint is called demand–supply balance given by

$$y_{j,n} = \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}_i} u_{i,l}^{j,n} x_{i,l} \quad \forall j \in \mathcal{J}; n \in \mathcal{N}_j \quad (4.5)$$

The left hand side of (4.5) is an aggregated quantity requested by a buyer  $j$  from a consumer group  $n \in \mathcal{N}_j$ . Groups are composed from consumers having a common attribute of interest to the buyer. For example, in the case of a TSO, each group includes customers connected to a common load point at the transmission level of a power system. In the case of a distributor, one group contains customers connected to a common load point of a feeder at the distribution level. For a retailer, a group is comprised of customers holding the same type of supply contracts. Consequently, each buyer  $j$  involves a corresponding set of customer groups (i.e.,  $\mathcal{N}_j$ ). Buyers, in general, require aggregated DR quantities from these groups and do not need to know exactly which customers are the providers.

On the right hand side of (4.5), all individual quantities  $x_{i,l}$  of those customers included in group  $n$  associated with buyer  $j$  are added together to form an aggregated supply corresponding to the demand  $y_{j,n}$ . Note also that  $l \in \mathcal{L}_i$  is the index of customers represented by the seller/aggregator  $i$ . Binary coefficient  $u_{i,l}^{j,n}$  is a relational status of each customer  $l$  to group  $n$ .  $u_{i,l}^{j,n}$  is 1 if the customer is included in the group, and 0 otherwise. A more detailed description of these variables and their notations is included in previous chapter.

In summary, Pareto efficiency in a DRX market can be obtained by solving the surplus optimization problem given by (4.4)–(4.5). Next subsection discusses how this problem can be solved.

### 4.3.2 Equivalent conditions

From a practical point of view, the Pareto optimization problem (4.4)–(4.5) could be centrally solved by the DRXO, using data reflecting benefit  $B_j$  and cost  $C_i$  collected from buyers and sellers, respectively. This is the case of a pool-based DRX developed in previous chapter. Such a centralized optimization, however, faces a major difficulty—participating agents may not be willing to provide the market operator with their own true information. For example, while a seller may “lie” by declaring an over-estimated cost for supplying DR, a buyer could declare an under-estimated benefit gained from DR trading. The aim here is to “game” the DRX market in a way that benefits a particular agent more than others. Such gaming behaviour would make market clearing difficult because the calculation of total surplus using (4.4) is no longer realistic due to incorrect cost and benefit data collected from the agents [98].

In a pool-based DRX market, the above information gaming issue can be mitigated using an assurance contract signed between buyers and sellers prior to the point of market clearing. Under this contract, agents will hurt themselves [in that their benefits are automatically reduced] if they untruthfully declare cost and benefit data [78–80]. This interesting

point signifies that the agents are better off not lie on purpose when sending information for market clearing. This “truth-revealing” advantage of an assurance contract, however, is only applicable to the case of pool-based market clearing where all relevant information are to be aggregated for a centralized profit optimization. In an agent-based DRX market where most private data is kept confidential by each agent and only used for their local optimizations, assurance contract approach is difficult to apply.

For this reason, rather than using an assurance contract and then directly solving the market clearing problem (4.4)–(4.5), we should convert it into an equivalent condition, and then solve this condition using a realistic mechanism considering the agent’s gaming behaviour. This conversion is based on the following proposition.

**Proposition 4.3.1** *Assuming that the cost function  $C_i$  is convex over  $x_{i,l}$  and the benefit function  $B_j$  is concave over  $y_{j,n}$ , the problem (4.4)–(4.5) is equivalent to the following conditions:*

$$\frac{\partial C_i}{\partial x_{i,l}} = \sum_{j \in \mathcal{J}} \sum_{n \in \mathcal{N}_j} u_{i,l}^{j,n} \frac{\partial B_j}{\partial y_{j,n}} \quad \forall i \in \mathcal{I}; l \in \mathcal{L}_i \quad (4.6)$$

$$y_{j,n} = \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}_i} u_{i,l}^{j,n} x_{i,l} \quad \forall j \in \mathcal{J}; n \in \mathcal{N}_j \quad (4.7)$$

**Proof** With the convexity of  $C_i$  and the concavity of  $B_j$ , the problem given by (4.4)–(4.5) belongs to a well-known class of convex optimization with affine (linear) equality constraints [99]. By Karush-Kuhn-Tucker (KKT) theorem, necessary and sufficient conditions for this optimality are

- (a)  $\partial L / \partial y_{j,n} = 0 \quad \forall j \in \mathcal{J}; n \in \mathcal{N}_j$
- (b)  $\partial L / \partial x_{i,l} = 0 \quad \forall i \in \mathcal{I}; l \in \mathcal{L}_i$
- (c)  $\partial L / \lambda_{j,n} = 0 \quad \forall j \in \mathcal{J}; n \in \mathcal{N}_j$

where  $L \triangleq (\sum_j B_j - \sum_i C_i) + \sum_j \sum_n [\lambda_{j,n}(y_{j,n} - \sum_i \sum_l u_{i,l}^{j,n} x_{i,l})]$  is called a Lagrange function and  $\lambda_{j,n}$  are called KKT multipliers. By taking partial derivatives of  $L$  in (a), (b), and (c), we imply the following:

- (d)  $-\lambda_{j,n} = \partial B_j / \partial y_{j,n}$
- (e)  $\partial C_i / \partial x_{i,l} = -\sum_j \sum_n u_{i,l}^{j,n} \lambda_{j,n}$
- (f)  $y_{j,n} = \sum_i \sum_l u_{i,l}^{j,n} x_{i,l}$

Combining (d) and (e) results in (4.6), while (f) is the same as (4.7). ■

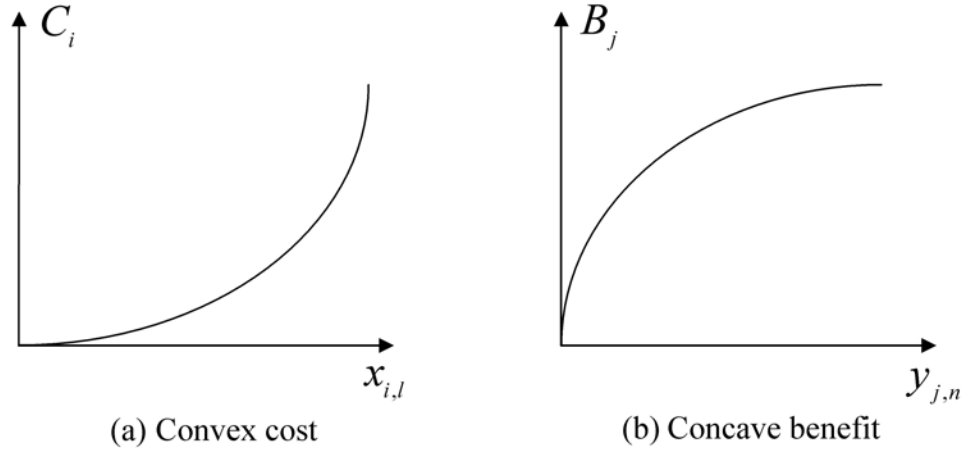


Figure 4.4: Assumptions on cost and benefit functions

**Remark** Equation (4.6) entails the marginal cost (measured by  $\partial C_i / \partial x_{i,l}$ ) associated with producing an individual quantity  $x_{i,l}$  by consumer  $l$ , must be equal to the sum of marginal benefits (measured by  $\partial B_j / \partial y_{j,n}$ ) gained by those buyers who jointly use this individual quantity. This equation is consistent with the well known Samuelson rule which is an alternative formalization of Pareto efficiency for optimal resource scheduling [100].

The mathematical derivation of (4.6)–(4.7) relies on two major assumptions—the convexity of  $C_i$  over  $x_{i,l}$  and the concavity of  $B_j$  over  $y_{j,n}$ . That is, for any  $t_1, t_2 \in [0, 1]$

- (a)  $C_i(t_1 x'_{i,l} + (1 - t_1) x''_{i,l}) \leq t_1 C_i(x'_{i,l}) + (1 - t_1) C_i(x''_{i,l}) \quad \forall x'_{i,l}, x''_{i,l}$
- (b)  $B_j(t_2 y'_{j,n} + (1 - t_2) y''_{j,n}) \geq t_2 B_j(y'_{j,n}) + (1 - t_2) B_j(y''_{j,n}) \quad \forall y'_{j,n}, y''_{j,n}$

These mathematical assumptions are illustrated by Fig. 4.4 where both  $C_i$  and  $B_j$  generally are increasing functions, but their exact trends are different. The former raises exponentially, meaning that the cost associated with producing an additional DR quantity increases at a higher rate than before. Benefit  $B_j$ , on the other hand, tends to be “saturate” with the increasing DR quantity.

In fact, the assumptions of cost convexity and benefit concavity are common in economic literature. For example, the generation cost in an electricity market is often modelled as a convex and quadratic curve to be used for the market design and analysis [101]. These assumptions will be discussed further in Section 4.5, for the DRX context.

### 4.3.3 Market equilibrium

Now, the market clearing objective becomes solving two equations (4.6) and (4.7) together. Solution to these equations is defined as a “market equilibrium” point where not only demand is balanced with supply, but also the marginal cost is matched by corresponding total marginal benefits. This equilibrium in a public goods market such as a DRX can be considered a generalization of those in a private goods market. (Private goods including

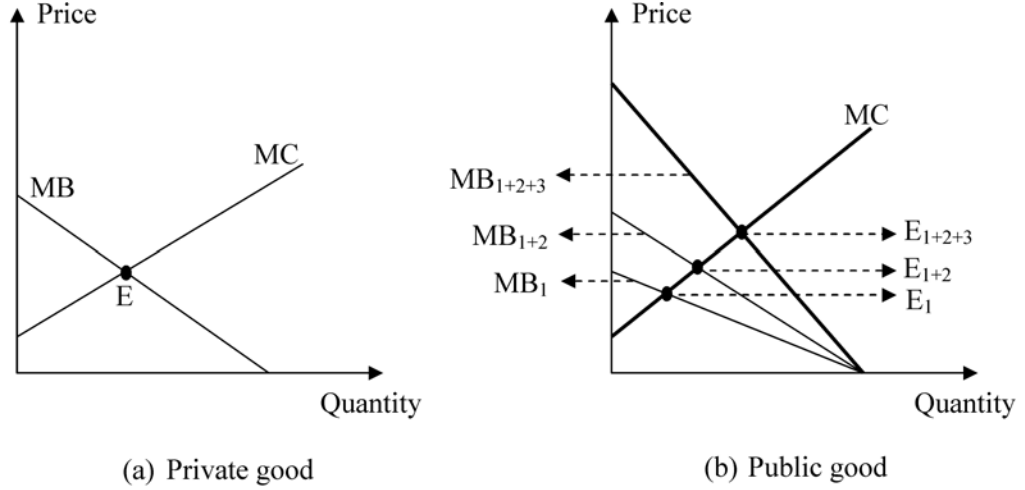


Figure 4.5: Equilibriums in different types of market

electricity are the usual kind of resource where each unit is consumed by only one agent, while public goods such as DR are special resources with each instant to be jointly used by multiple agents)

Fig. 4.5 illustrates the equilibrium concept in different types of markets. In a private good market, the equilibrium point (E) can be obtained by simply matching a demand curve [representing marginal benefit (MB)] with a supply curve [representing marginal cost (MC)], in which both a quantity and a price for the private good are balanced. In a public good market, the equilibrium concept is rather complex with multiple demand curves from different buyers who jointly purchase the good from a seller. As can be seen from Fig. 4.5, the demand curve of the first buyer is given by  $MB_1$ . When combining the demand curves of the first and second buyers, we have  $MB_{1+2}$ , and so on. Supposing that there are three buyers (i.e., a Transco, a Disco, a Reco in a DRX), then the globally efficient market equilibrium [where all buyers together pay for the public good] is  $E_{1+2+3}$ , given by the intersection of the aggregated demand and individual supply curves. This equilibrium outcome is also described by our developed Pareto-efficient conditions, (4.6) and (4.7), where the DR marginal cost ( $\frac{\partial C_i}{\partial x_{i,l}}$ ) is matched by the sum of all relevant DR marginal benefits ( $\frac{\partial B_j}{\partial y_{j,n}}$ ). If only one buyer pay while the others “ride” the public good for free, the resulting equilibrium point is, for instance,  $E_1$  which is *not* an efficient market outcome [75].

The most important properties of an equilibrium point are its “existence” and “uniqueness” in the market. If such an equilibrium does not exist, the DRX market cannot be cleared using conditions (4.6) and (4.7). On the other hand, the absence of the uniqueness property leads to a situation of “multiple equilibria”. In which case, one will have to select the best among multiple equilibrium solutions [95,98]. Such a selection, however, is beyond the scope of this thesis.

**Proposition 4.3.2** *Assuming that the cost function  $C_i$  is “strictly” convex over  $x_{i,l}$  and the benefit function  $B_j$  is “strictly” concave over  $y_{j,n}$ , the DRX market equilibrium described by (4.6)—(4.7) exists and is unique.*

**Proof** Proving the existence of market equilibrium is not difficult from a mathematical point of view. According to the KKT theorem [99], since the problem (4.4)—(4.5) is a convex optimization with affine constraints, it must have at least one solution that is also a solution to the equilibrium equations (4.6)—(4.7). In other words, an equilibrium point always exists in a DRX market. ■

A more detailed proof for this existence using “fixed-point theorems” [that is fundamental to algebraic topology such as Fig. 4.5 can be found in a well-known paper on microeconomics [102]. Note also that in standard convex optimization, any local solution is necessarily a global solution [99]. This proposition implies that all solutions to (4.6)—(4.7) achieve the same level of optimality.

Now we prove the uniqueness of the DRX market equilibrium by contradiction. By assuming there are at least two equilibrium points  $\mathbf{q}^*$  and  $\mathbf{q}^\star$  ( $\mathbf{q} \triangleq [\dots, y_{j,n}, \dots, x_{i,l}, \dots]$ ) satisfying conditions (4.6)—(4.7) and thus achieving Pareto optimality given by (4.4)—(4.5), we assert that

$$(a) \ S(\mathbf{q}^*) = S(\mathbf{q}^\star) = \max \{S(\mathbf{q})\}_{\mathbf{q} \in \mathcal{Q}}$$

where  $S \triangleq \sum_j B_j - \sum_i C_i$  is the total market surplus—the objective value,  $\mathcal{Q}$  is the set of all  $\mathbf{q}$  satisfying condition (4.5). Since (4.5) has an affine form,  $\mathcal{Q}$  is a convex set [99]. (Which can be easily proven using convexity definition).

On the other hand, since  $S(\mathbf{q})$  is a *strictly* concave function over  $\mathbf{q}$ ,  $tS(\mathbf{q}^*) + (1 - t)S(\mathbf{q}^\star) < S(t\mathbf{q}^* + (1 - t)\mathbf{q}^\star)$  for any  $t \in (0, 1)$ , by concavity definition. However  $S(\mathbf{q}^*) = S(\mathbf{q}^\star)$ , then

$$(b) \ S(\mathbf{q}^*) < S(t\mathbf{q}^* + (1 - t)\mathbf{q}^\star)$$

$$(c) \ S(\mathbf{q}^\star) < S(t\mathbf{q}^* + (1 - t)\mathbf{q}^\star)$$

Since  $(t\mathbf{q}^* + (1 - t)\mathbf{q}^\star)$  is another point belonging to the convex set  $\mathcal{Q}$ , conditions (b)—(c) contradicts with conditions (a) where both  $\mathbf{q}^*$  and  $\mathbf{q}^\star$  are globally optimal in  $\mathcal{Q}$ . Consequently, there cannot be more than one equilibrium point in the market. Combining this property with the existence proposition given above, we conclude the uniqueness of DRX market equilibrium. ■

**Remark** The proof of equilibrium uniqueness relies the assumed strict concavity of the total market surplus,  $S(\mathbf{q})$ . If  $S(\mathbf{q})$  is only a non-strictly concave function (by virtue of  $C_i$  being non-strictly convex and  $B_j$  non-strictly concave), the ‘<’ sign in conditions (b)—(c)

is replaced by ' $\leq$ '. In this case, these conditions do not necessarily contradict condition (a). This means the DRX market may have *multiple* equilibria.

These mathematical assumptions are not as strict as their names suggest. In fact, they were commonly adopted for many economic studies found in the literature, for instance, the analysis of electricity markets [6, 98, 101]. Generally concavity and strict concavity [or convexity and strict convexity] are closely related conditions. If a function is both concave and increasing over its variable, it becomes strictly concave. This is the case of a benefit function,  $(B_j)$ , shown in Fig. 4.4–b.

## 4.4 Walrasian auction design

With a solid mathematical background [for the DRX market clearing problem] developed in the above section, here we design an effective auction mechanism that coordinate agents [with their local profit optimizations] towards achieving market equilibrium with Pareto efficiency. First we present overall description of the mechanism, and then we will focus on technical details.

### 4.4.1 Overall design scheme

The proposed market clearing mechanism is shown in Fig. 4.6, following a *radial* agent-based structure in market design. Particularly the DRXO plays the role of being a central node to communicate information with all [self-interested] economic agents, including buyers (the Transco, Recos, and Discos) and sellers (ESCOs on behalf of electricity customers). Here direct information exchange between any two agents is not allowed.

The overall idea of the proposed mechanism is to employ *Walrasian auctions* in the form of multi-round demand–supply balancing price adjustments [75]. That is, the DRX adjusts DR prices to “drive” both buyer demand and seller supply in a prescribed way that converges to the market equilibrium at the point where demand is balanced with supply. As shown in Fig. 4.6, the multi-round auctions are based on an iterative procedure where buying and selling agents update their demand quantity bids and supply quantity offers, in response to DR prices issued from the DRXO at every round. Such auctions allow the agents to maximize their own (local) benefits to derive appropriate bids and offers under given prices.

### 4.4.2 Price adjustment methods

Using DR quantity bids and offers collected from agents, the DRXO adjusts prices for the next round. Here the price adjustment is based on a pre-specified market clearing rule, with the aim of matching the demand with the supply [75]. Particularly if the quantities

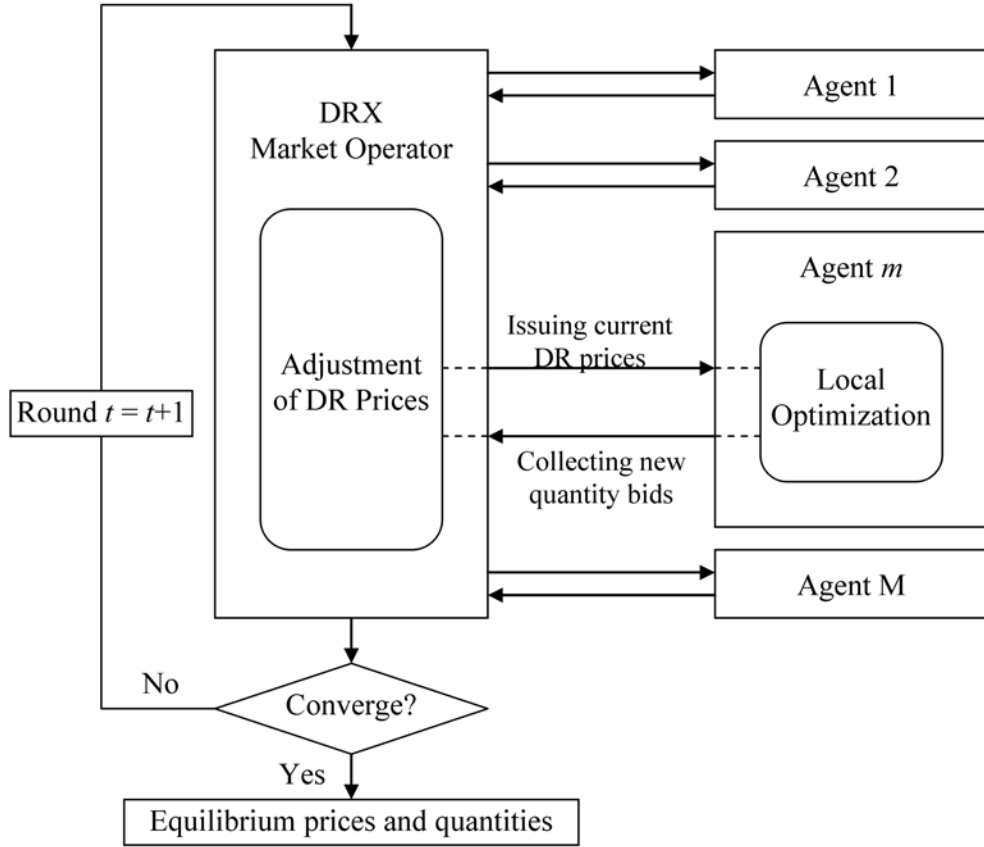


Figure 4.6: The proposed multi-round market clearing mechanism

demanded by buying agents are higher than those offered by selling agents, prices will be increased by the DRXO. According to the law of demand and supply, when faced with higher prices, buyers reduce their high demand bids while sellers increase their low supply offers [98]. These actions reduce the gap between demand and supply. Alternatively when demand quantities are lower than supply quantities, the DRXO will reduce the prices to increase demand and decrease supply.

Price adjustment, under the above market clearing rule for demand-supply balancing, can be performed using either classical or Newton tâtonnement methods.

### Classical tâtonnement

Tâtonnement is a form of hill-climbing algorithm proposed by Leon Walras [16] which is the most popular price adjustment method in market design. Mathematically, it can be defined as follows:

$$p_{j,n}^{t+1} = p_{j,n}^t + Kz_{j,n}^t \quad \forall j \in \mathcal{J}; n \in \mathcal{N}_j \quad (4.8)$$



$$z_{j,n}^t = y_{j,n}^t - \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}_i} u_{i,l}^{j,n} x_{i,l}^t \quad (4.9)$$

$$p_{i,l}^{t+1} = \sum_{j \in \mathcal{J}} \sum_{n \in \mathcal{N}_j} u_{i,l}^{j,n} p_{j,n}^{t+1} \quad \forall i \in \mathcal{I}; l \in \mathcal{L}_i \quad (4.10)$$

In (4.8),  $p_{j,n}$  is the price to be paid by agent  $j$  for buying aggregated quantity  $y_{j,n}$ .  $z_{j,n}$  is the *aggregated excess demand* that represents an imbalance between the corresponding demand and supply, as described by (4.9). The price adjustment in (4.8) is considered *proportional* to the excess demand by the factor  $K > 0$ . In (4.10),  $p_{i,l}$  is the price received by seller  $i$  for supplying individual quantity  $x_{i,l}$ . This price is the sum of prices paid by those buyers jointly using this quantity. Note that in all equations above,  $t$  and  $t + 1$  index the bidding round.

The major advantage of using these equations for price adjustment is that **no data associated with the cost and benefit for agents is required**. Rather, the adjustment relies solely on the parameter  $K$  which can be chosen by the DRXO. This property avoids the gaming opportunities mentioned above.

Classical tâtonnement is generally simple, but has the drawback that it might not work in some special cases [103]. As will be analyzed in the next section, if the value of  $K$  is not chosen correctly, the adjusted price will not converge to an equilibrium point where supply meets demand. For this reason, besides choosing carefully the parameter  $K$ , there should be a backup method for price adjustment in the case that  $K$  is too difficult to determine.

### Newton tâtonnement

The Newton method is similar to classical tâtonnement, except that the price updating rule (4.8) is replaced, while (4.9) and (4.10) remain unchanged. The rule (4.8) is based on the Newton numerical method for solving nonlinear algebraic equations [104]:

$$\mathbf{p}^{t+1} = \mathbf{p}^t - (\mathbf{J}^t)^{-1} \cdot \mathbf{z}(\mathbf{p}^t) \quad (4.11)$$

where  $\mathbf{z}$  is a vector comprised of all aggregated excess demand  $z_{j,n}$ , and  $\mathbf{p}$  is a vector comprised of all buyer prices  $p_{j,n}$ ,  $\forall j \in \mathcal{J}$  and  $\forall n \in \mathcal{N}_j$ .  $\mathbf{J}$  is a Jacobian matrix comprised of all first-order partial derivatives of  $\mathbf{z}$  with respect to  $\mathbf{p}$ .  $\mathbf{J}$  has dimensions of  $N \times N$  where  $N = \sum_j |\mathcal{N}_j|$ .

Mathematically, (4.11) attempts to iteratively solve the nonlinear equation  $\mathbf{z} = 0$ , where  $\mathbf{z}$  is considered a function of price variable  $\mathbf{p}$  (i.e.,  $\mathbf{z} = \mathbf{z}(\mathbf{p})$ ). Solution to this equation is the point where supply meets demand, which is the objective of price adjustment.

To illustrate the Newton tâtonnement method with a Jacobian matrix, we consider a very small power system given by Fig. 4.7. The system is comprehensive to the extent that it includes both transmission and distribution networks corresponding to a wholesale

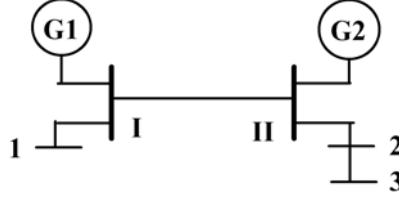


Figure 4.7: Small power system for demonstrating the Newton pricing method. Here each feeder load point (1, 2,...,5) supplies power for a small geographical area such as suburbs

and a retail electricity markets, respectively. The transmission network is operated by a Transco, while the distribution run by a Disco. There are also a Reco and an ESCo—each deals with all electricity customers. Under these structural arrangements, we define the DRX as follows:  $\mathcal{J} = \{\text{Transco}, \text{Disco}, \text{Reco}\}$ —the set of DR buyers;  $\mathcal{N}_{\text{Transco}} = \{\text{I}, \text{II}\}$   $\mathcal{N}_{\text{Disco}} = \{1, 2, 3\}$ , and  $\mathcal{N}_{\text{Reco}} = \{\text{A}\}$  where A is the only type of retail contracts offered to all customers. On the other side of the DRX market,  $\mathcal{I} = \{\text{ESCo}\}$ —the set of all DR sellers and  $\mathcal{L}_{\text{ESCo}} = \{1, 2, 3\}$ . In this case, the price and aggregated excess demand vector is given by:

$$\mathbf{p} = [p_{\text{Transco}, \text{I}}, p_{\text{Transco}, \text{II}}, p_{\text{Disco}, 1}, p_{\text{Disco}, 2}, p_{\text{Disco}, 3}, p_{\text{Reco}, \text{A}}]$$

$$\mathbf{z} = [z_{\text{Transco}, \text{I}}, z_{\text{Transco}, \text{II}}, z_{\text{Disco}, 1}, z_{\text{Disco}, 2}, z_{\text{Disco}, 3}, z_{\text{Reco}, \text{A}}]$$

Then, the Jacobian matrix of  $\mathbf{z}$  over  $\mathbf{p}$  [in Newton price tâtonnement] is given by

$$\mathbf{J} = \begin{pmatrix} \frac{\partial z_{\text{Transco}, \text{I}}}{\partial p_{\text{Transco}, \text{I}}} & \frac{\partial z_{\text{Transco}, \text{I}}}{\partial p_{\text{Transco}, \text{II}}} & \frac{\partial z_{\text{Transco}, \text{I}}}{\partial p_{\text{Disco}, 1}} & \frac{\partial z_{\text{Transco}, \text{I}}}{\partial p_{\text{Disco}, 2}} & \frac{\partial z_{\text{Transco}, \text{I}}}{\partial p_{\text{Disco}, 3}} & \frac{\partial z_{\text{Transco}, \text{I}}}{\partial p_{\text{Reco}, \text{A}}} \\ \frac{\partial z_{\text{Transco}, \text{II}}}{\partial p_{\text{Transco}, \text{I}}} & \frac{\partial z_{\text{Transco}, \text{II}}}{\partial p_{\text{Transco}, \text{II}}} & \frac{\partial z_{\text{Transco}, \text{II}}}{\partial p_{\text{Disco}, 1}} & \frac{\partial z_{\text{Transco}, \text{II}}}{\partial p_{\text{Disco}, 2}} & \frac{\partial z_{\text{Transco}, \text{II}}}{\partial p_{\text{Disco}, 3}} & \frac{\partial z_{\text{Transco}, \text{II}}}{\partial p_{\text{Reco}, \text{A}}} \\ \frac{\partial z_{\text{Disco}, 1}}{\partial p_{\text{Transco}, \text{I}}} & \frac{\partial z_{\text{Disco}, 1}}{\partial p_{\text{Transco}, \text{II}}} & \frac{\partial z_{\text{Disco}, 1}}{\partial p_{\text{Disco}, 1}} & \frac{\partial z_{\text{Disco}, 1}}{\partial p_{\text{Disco}, 2}} & \frac{\partial z_{\text{Disco}, 1}}{\partial p_{\text{Disco}, 3}} & \frac{\partial z_{\text{Disco}, 1}}{\partial p_{\text{Reco}, \text{A}}} \\ \frac{\partial z_{\text{Disco}, 2}}{\partial p_{\text{Transco}, \text{I}}} & \frac{\partial z_{\text{Disco}, 2}}{\partial p_{\text{Transco}, \text{II}}} & \frac{\partial z_{\text{Disco}, 2}}{\partial p_{\text{Disco}, 1}} & \frac{\partial z_{\text{Disco}, 2}}{\partial p_{\text{Disco}, 2}} & \frac{\partial z_{\text{Disco}, 2}}{\partial p_{\text{Disco}, 3}} & \frac{\partial z_{\text{Disco}, 2}}{\partial p_{\text{Reco}, \text{A}}} \\ \frac{\partial z_{\text{Disco}, 3}}{\partial p_{\text{Transco}, \text{I}}} & \frac{\partial z_{\text{Disco}, 3}}{\partial p_{\text{Transco}, \text{II}}} & \frac{\partial z_{\text{Disco}, 3}}{\partial p_{\text{Disco}, 1}} & \frac{\partial z_{\text{Disco}, 3}}{\partial p_{\text{Disco}, 2}} & \frac{\partial z_{\text{Disco}, 3}}{\partial p_{\text{Disco}, 3}} & \frac{\partial z_{\text{Disco}, 3}}{\partial p_{\text{Reco}, \text{A}}} \\ \frac{\partial z_{\text{Reco}, \text{A}}}{\partial p_{\text{Transco}, \text{I}}} & \frac{\partial z_{\text{Reco}, \text{A}}}{\partial p_{\text{Transco}, \text{II}}} & \frac{\partial z_{\text{Reco}, \text{A}}}{\partial p_{\text{Disco}, 1}} & \frac{\partial z_{\text{Reco}, \text{A}}}{\partial p_{\text{Disco}, 2}} & \frac{\partial z_{\text{Reco}, \text{A}}}{\partial p_{\text{Disco}, 3}} & \frac{\partial z_{\text{Reco}, \text{A}}}{\partial p_{\text{Reco}, \text{A}}} \end{pmatrix}.$$

From  $\mathbf{p}$ ,  $\mathbf{z}$ , and  $\mathbf{J}$ , one can construct the iterative equation for Newton tâtonnement, as given by (4.11).

The main advantage of using the Newton method is that it guarantees fast convergence in most cases [104]. This advantage compensates for the limitation of classical tâtonnement

as discussed above. However, the Newton method requires knowledge about the Jacobian matrix  $\mathbf{J}$ , which must be based on private data collected from participating agents [95]. This, again, raises concerns about gaming behavior as the agents may ‘lie’ about their data. For this reason, rather than collecting data from agents, the DRXO should use its own observations from agents’ past responses to given prices to estimate the Jacobian matrix. For example, by regressing historical data for quantity bids with respect to different prices, the DRXO can produce an estimated quantity-price curve. From such synthesised curves, the Jacobian matrix  $\mathbf{J}$  can be derived [98]. This aspect will be analysed further via numerical study.

The Newton method with an estimated Jacobian matrix is an inexact method. The next section shows that this method, under some conditions, will converge to the same point as the exact Newton method.

## 4.5 Robustness evaluation

To prove that the proposed agent-based market clearing mechanism using either classical or Newton price tâtonnements is robust in the sense that it always converges to a unique Pareto-efficient market equilibrium, we must show that both conditions (4.6) and (4.7) are satisfied when the market is settled. First, we examine condition (4.6) which is related to a local optimization performed by each agent in the market. We also discuss how self-interested agents optimally respond to a price signal under given market clearing rules. Then, the convergence of tâtonnement methods towards condition (4.7) is analysed.

### 4.5.1 Agent local optimization

#### Myopic situation

In the proposed mechanism with a radial structure, all communications must go through the DRXO as a central node. Therefore, agents cannot collect private information directly from each other. The only information available to each agent and issued by the DRXO, is the price of DR quantities they intend to buy or sell. Under this market arrangement, it would be certainly very hard for any agent to anticipate actions taken by other agents to increase their local benefits [105]. Such a situation is referred to in economic literature as “myopia”, in that a local agent cannot see what happens outside.

There are two common approaches [for an agent to deal with myopic situation when optimizing its local profit] including statistical and guidance-based [106]. The former aims at modeling the actions taken by other [competing] agents, using stochastic methods due to lack of relevant information. For example, the myopic trading in financial markets, under multiple sources of uncertainties (i.e., volatilities) over time and across all agents, often relies heavily on statistical modeling [5, 8, 9, 73, 105]. Despite its advantages, the statistical

approach cannot be completely realistic, consequently causing some risks incurred by those agents who use such an approach. For instance, many financial crises over the world can be explained by the underestimated market volatilities [9, 73]. Due to these uncertainties, any agent is better off using an alternative [myopic] approach, that is, to follow the guidance of a designated market operator who has some information of other agents [105]. In the context of a DRX, both buying and selling agents can myopically follow the market price issued from the DRXO as an agent guider. In other words, each agent under the proposed mechanism is considered as a price-taker.

### Optimization convexifying

Accepting prices issued by the DRXO, each buying agent  $j$  performs local profit optimization at every market clearing round  $t$ , as follows:

$$\max \left\{ B_j^t - \sum_{n \in \mathcal{N}_j} p_{j,n}^t y_{j,n}^t \right\} \quad \forall j \in \mathcal{J} \quad (4.12)$$

Similarly, each price-taking selling agent  $i$  performs local optimization according to:

$$\max \left\{ \sum_{l \in \mathcal{L}_i} p_{i,l}^t x_{i,l}^t - C_i^t \right\} \quad \forall i \in \mathcal{I} \quad (4.13)$$

In (4.12) and (4.13),  $p_{i,l}^t$  and  $p_{j,n}^t$  are constants, while  $x_{i,l}^t$  and  $y_{j,n}^t$  are treated as optimization variables under the corresponding agent.  $C_i^t$  and  $B_j^t$  are the DR cost and benefit that are functions of those variables, respectively. Note that these functions must be kept private by agents. In a DRX market with radial communication structure, agents are not allowed to exchange information directly with each other.

Generally, the problems given by (4.12) and (4.13) may be non-convex, and thereby, having either multiple solutions, one solution, or even no solution at all [99]. These cases together unnecessarily complicate the agent local optimizations and then the whole market clearing mechanism. Hence, there is a need for proposing a “convexifying rule” as given by Fig. 4.8, where all agents are required to approximate their DR costs [or DR benefits] as strictly convex [or concave] functions to be embedded within the local optimizations. If such a rule can be successfully applied, it is not only the problems (4.13) and (4.12) that have unique solutions but also the whole DRX market that have a unique equilibrium point as was proven above.

Convexification is not a theoretical limitation of the proposed agent-based mechanism but a practical necessity for achieving a desired market outcome with unique equilibrium solution. From local agents perspective, the convexifying rule keeps their optimizing task simple. In fact, such rules have long been discussed in electricity markets as an important tool to deal with the non-convexity issues in generating unit commitment [107].

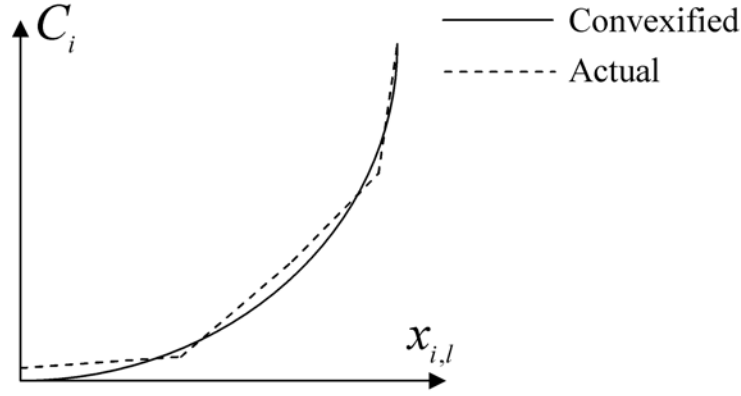


Figure 4.8: Convexification as an approximation tool

Under convexification, rational agents choose the optimal DR quantities to buy or sell following (4.12) or (4.13), as given by:

$$p_{j,n}^t = \frac{\partial B_j^t}{\partial y_{j,n}^t} \quad \forall j \in \mathcal{J}; n \in \mathcal{N}_j \quad (4.14)$$

$$p_{i,l}^t = \frac{\partial C_i^t}{\partial x_{i,l}^t} \quad \forall i \in \mathcal{I}; l \in \mathcal{L}_i \quad (4.15)$$

Equation (4.14) implies that rational buyers will increase their demand up to the point at which the marginal benefits they gain from DR are equal to the corresponding prices they have to pay. Equation (4.15), on the other hand, implies that rational sellers will increase their DR provisions up to the point at which the marginal costs of producing these DRs are equal to the corresponding prices they receive. These observed buying and selling behaviours are consistent with microeconomic theory [75].

By substituting both (4.14) and (4.15) into (4.10) we obtain:

$$\frac{\partial C_i^t}{\partial x_{i,l}^t} = \sum_{j \in \mathcal{J}} \sum_{n \in \mathcal{N}_j} u_{i,l}^{j,n} \frac{\partial B_j^t}{\partial y_{j,n}^t} \quad \forall i \in \mathcal{I}; l \in \mathcal{L}_i \quad (4.16)$$

Equation (4.16) implies that market clearing at every round  $t$  satisfies (4.6)—one of the two conditions of Pareto efficiency. With this condition satisfied, the remaining issue of the mechanism evaluation is to demonstrate that market clearing always converges to a unique equilibrium point satisfying a demand supply balance given by (4.7)—the other condition of Pareto optimality.

#### 4.5.2 Convergence analysis

##### Classical tâtonnement

Here we determine values of the price adjustment factor  $K$  at which market clearing using (4.8)–(4.10) will converge. Let  $\mathbf{e}^t = \mathbf{p}^t - \mathbf{p}^*$  be the price error at iteration  $t$  with reference to the equilibrium price  $\mathbf{p}^*$ . Then,

**Proposition 4.5.1** *The convergence rate of classical price tâtonnement is given by*

$$\|\mathbf{e}^{t+1}\| \leq \|\mathbf{I} + K\mathbf{J}^*\| \cdot \|\mathbf{e}^t\| \quad (4.17)$$

where  $\mathbf{J}^*$  is [like (4.11)] the Jacobian matrix of  $\mathbf{z}$  with respect to the price variable  $\mathbf{p}$ , evaluated at  $\mathbf{p}^*$ .  $\mathbf{I}$  is the unit matrix of the same size as  $\mathbf{J}^*$ . Also  $\|\cdot\|$  denotes the Euclidean norm of a vector or matrix.

**Proof** We sketch a proof for the convergence rate (4.17) of classical tâtonnement. Rewriting the price updating rule (4.8) in a vector form we obtain  $\mathbf{p}^{t+1} = \mathbf{p}^t + K \cdot \mathbf{z}(\mathbf{p}^t)$ . Then,

$$(a) \quad \mathbf{e}^{t+1} = \mathbf{e}^t + K \cdot \mathbf{z}(\mathbf{p}^t)$$

By a geometric theorem on tangent representation [104], the differentiable function  $\mathbf{z}(\mathbf{p})$  is given as follows:

$$(b) \quad \mathbf{z}(\mathbf{p}) = \mathbf{z}(\mathbf{p}^*) + \mathbf{J}^*(\mathbf{p} - \mathbf{p}^*) + \mathbf{R}$$

where  $\mathbf{J}^*$  is a first-derivative Jacobian matrix evaluated at  $\mathbf{p}^*$ ,  $\mathbf{R}$  is a residual term representing the difference between the surface  $\mathbf{z}(\mathbf{p})$  and its tangent plane  $\mathbf{z}(\mathbf{p}^*) + \mathbf{J}^*(\mathbf{p} - \mathbf{p}^*)$  at any point  $\mathbf{p}$  within the  $N$ -dimension Euclidean space. Such a difference becomes smaller when  $\mathbf{p}$  approaches  $\mathbf{p}^*$ .

Since, in a DRX market, the price  $\mathbf{p}^t$  oscillates around its equilibrium point  $\mathbf{p}^*$ , the corresponding residual term  $\mathbf{R}$  can be assumed small. Then  $\mathbf{z}(\mathbf{p}^t) \approx \mathbf{J}^*(\mathbf{p}^t - \mathbf{p}^*)$ . (Note that  $\mathbf{z}(\mathbf{p}^*) = 0$ .) Substituting this equation into (a), we obtain  $\|\mathbf{e}^{t+1}\| = \|(\mathbf{I} + K\mathbf{J}^*) \cdot \mathbf{e}^t\|$ . Consequently we assert (4.17). ■

**Remark** Equation (4.17) suggests that the price adjustment error changes *linearly* after each iteration. This linear trend implies that  $\|\mathbf{e}^t\| \leq \|\mathbf{I} + K\mathbf{J}^*\|^t \cdot \|\mathbf{e}^0\|$  for any  $t > 0$ . Then a sufficient condition for price convergence (i.e.,  $\|\mathbf{e}^t\| \rightarrow 0$  as  $t \rightarrow +\infty$ ) is given as follows,

$$\|\mathbf{I} + K\mathbf{J}^*\| < 1 \quad (4.18)$$

Condition (4.18) can be satisfied by choosing appropriate values for the price adjustment factor  $K$ . However, as similar to the Newton method, the main issue here is that the DRXO cannot determine the exact Jacobian matrix  $\mathbf{J}^*$  due to the lack of private cost and benefit data from participating agents. Therefore, the DRXO uses historical data to estimate  $\mathbf{J}^*$  such that  $K$  is determined appropriately. Note also that rather than finding

the exact values of  $\mathbf{K}$ , the DRXO only needs to know the feasible range to satisfy condition (4.18). This simplifies the task of parameter estimation.

However, as suggested by economists, there are some special cases where price adjustment using classical tâtonnement cannot converge [103]. This issue arises when  $\|\mathbf{I} + \mathbf{K}\mathbf{J}^*\| \geq 1$  for any chosen/estimated value of  $\mathbf{K}$ , causing prices to diverge. In such cases, the Newton method must be used instead.

### Newton tâtonnement

Here we examine the conditions under which price adjustment using the inexact Newton method converges. Let  $\Delta^t$  be the error in estimating the inverse Jacobian matrix  $(\mathbf{J}^t)^{-1}$  in the price updating rule (4.11). (Note that  $\Delta^t$  also has size  $N \times N$ .) Then,

**Proposition 4.5.2** *The convergence rate of the proposed Newton pricing method is*

$$\|\mathbf{e}^{t+1}\| \leq (L\|\Delta^t\| + M\|\mathbf{e}^t\|)\|\mathbf{e}^t\| \quad (4.19)$$

where  $L = \|\mathbf{J}\|^U$  (this denotes the upper bound of  $\|\mathbf{J}\|$ );  $M = \frac{1}{2}\|\mathbf{J}^{-1}\|^U\|\mathbf{H}\|^U$  with  $\mathbf{H}$  being a Hessian matrix comprised of all second-order partial derivatives of  $\mathbf{z}(\mathbf{p})$ .

**Proof** Here we derive condition (4.19) that represents the convergence rate of the proposed inexact Newton method. By adding the error  $\Delta^t$  of estimating  $\mathbf{J}^{-1}$  to the price adjustment equation (4.11), we obtain  $\mathbf{p}^{t+1} = \mathbf{p}^t - [(\mathbf{J}^t)^{-1} + \Delta^t] \cdot \mathbf{z}(\mathbf{p}^t)$ . Then,

$$(a) \quad \mathbf{e}^{t+1} = \mathbf{e}^t - [(\mathbf{J}^t)^{-1} + \Delta^t] \cdot \mathbf{z}(\mathbf{p}^t)$$

Assuming that  $\mathbf{z}(\mathbf{p})$  is twice differentiable, then its value at the equilibrium point  $\mathbf{p}^*$  can be expressed in terms of a second-order Taylor series expansion around any arbitrary point  $\mathbf{p}$  [104]. In particular,

$$(b) \quad \mathbf{z}(\mathbf{p}^*) = \mathbf{z}(\mathbf{p}^t) + \mathbf{J}^t(\mathbf{p}^* - \mathbf{p}^t) + \frac{1}{2}(\mathbf{p}^* - \mathbf{p}^t)^T \mathbf{H}^\xi(\mathbf{p}^* - \mathbf{p}^t)$$

where  $(\mathbf{p}^* - \mathbf{p}^t)^T$  is the transpose of  $(\mathbf{p}^* - \mathbf{p}^t)$ .  $\mathbf{H}^\xi$  is the Hessian matrix evaluated at some  $\mathbf{p}^\xi$  between  $\mathbf{p}$  and  $\mathbf{p}^*$ . Since  $\mathbf{z}(\mathbf{p}^*) = 0$ ,  $\mathbf{z}(\mathbf{p}^t) = \mathbf{J}^t \mathbf{e}^t - \frac{1}{2}(\mathbf{e}^t)^T \mathbf{H}^\xi \mathbf{e}^t$ . Substituting this equation into (a), we obtain

$$\begin{aligned} \|\mathbf{e}^{t+1}\| &= \|\Delta^t \mathbf{J}^t \mathbf{e}^t - \frac{1}{2}(\mathbf{e}^t)^T [(\mathbf{J}^t)^{-1} + \Delta^t] \mathbf{H}^\xi \mathbf{e}^t\| \\ &\leq \|\Delta^t \mathbf{J}^t \mathbf{e}^t\| + \|\frac{1}{2}(\mathbf{e}^t)^T [(\mathbf{J}^t)^{-1} + \Delta^t] \mathbf{H}^\xi \mathbf{e}^t\| \\ &\leq \|\Delta^t\| \cdot \|\mathbf{J}^t\| \cdot \|\mathbf{e}^t\| + \frac{1}{2}\|(\mathbf{J}^t)^{-1} + \Delta^t\| \cdot \|\mathbf{H}^\xi\| \cdot \|(\mathbf{e}^t)\|^2 \\ \therefore \|\mathbf{e}^{t+1}\| &\leq (L\|\Delta^t\| + M\|\mathbf{e}^t\|)\|\mathbf{e}^t\| \end{aligned}$$

where  $L \triangleq \|\mathbf{J}^t\|^U = \|\mathbf{J}\|^U$ ,  $M \triangleq \frac{1}{2}\|(\mathbf{J}^t)^{-1} + \Delta^t\|^U \cdot \|\mathbf{H}^\xi\|^U = \frac{1}{2}\|\mathbf{J}^{-1}\|^U \cdot \|\mathbf{H}\|^U$ , assuming that  $\|\mathbf{J}\|$ ,  $\|\mathbf{J}^{-1}\|$ , and  $\|\mathbf{H}\|$  are all upper bounded. ■

**Remark** Equation (4.19) implies that the price adjustment error  $\mathbf{e}^t$  changes quadratically in each iteration. This quadratic trend, in the case that  $\Delta^t = 0$  for every  $t$ , corresponds to an exact Newton method that converges rapidly to the equilibrium solution [104].

Now we consider the case of  $\Delta^t \neq 0$ . A sufficient condition for convergence is that the first factor on the right hand side of (4.19),  $(L\|\Delta^t\| + M\|\mathbf{e}^t\|)$ , is less than 1 for any  $t$ . This condition ensures that the error  $\|\mathbf{e}^t\|$  decreases after each iteration, consequently approaching zero as  $t \rightarrow +\infty$  [104].

For  $(L\|\Delta^t\| + M\|\mathbf{e}^t\|) < 1$ ,  $\|\Delta^t\|$  and  $\|\mathbf{e}^t\|$  should be limited as both  $L$  and  $M$  are fixed constants. While  $\|\Delta^t\|$  can be reduced by estimating more accurately the Jacobian matrix  $\mathbf{J}^t$  using current market data,  $\|\mathbf{e}^t\|$  depends on  $\|\mathbf{e}^0\|$  and the price  $\mathbf{p}^0$  that is initiated by the DRXO. In general, if the initiation is sufficiently close to the equilibrium point, price adjustment in subsequent iterations will converge quickly to this point. Otherwise, the price adjustment may either not converge or converge at a slower rate.

We formalize the term “sufficiently close” as the following particular condition to be used for price initiation:

$$L\|\Delta^t\|^U + M\|\mathbf{e}^0\| < 1 \quad (4.20)$$

$$\text{or } \|\mathbf{e}^0\| < \frac{1 - L\|\Delta^t\|^U}{M} \quad (4.21)$$

This condition alone is sufficient for the method to converge. If the condition holds, then  $\|\mathbf{e}^1\| < \|\mathbf{e}^0\|$  by (4.19). This implies  $\|\mathbf{e}^1\|$  also satisfies (4.21), then  $\|\mathbf{e}^2\| < \|\mathbf{e}^1\|$ , etc. Therefore,  $\|\mathbf{e}^t\|$  is a decreasing sequence, which approaches zero. In fact, condition (4.20) is a stricter version of the above mentioned condition,  $(L\|\Delta^t\| + M\|\mathbf{e}^t\|) < 1$ , as the former can imply the latter.

Although (4.20) is a strict condition, it is easy to implement. Specifically, by using historical data, the DRXO can determine the upper bounds  $L$ ,  $M$ , and  $\|\Delta^t\|^U$  *offline*. From these pre-determined parameters,  $\mathbf{p}^0$  can be initiated satisfying condition (4.21).

Besides price initiation, care must be taken estimating the Jacobian matrix  $\mathbf{J}$ . If the error  $\Delta^t$  is larger, the initial value  $\mathbf{e}^0$  must be smaller for the method to converge by condition (4.21). Achieving such a initiation closer to the equilibrium is obviously more difficult, as the DRXO does not know exactly the position of such an equilibrium point. Hence, a reasonable estimation of the Jacobian matrix, resulting in a relatively small error  $\Delta^t$  for every  $t$ , is also necessary.



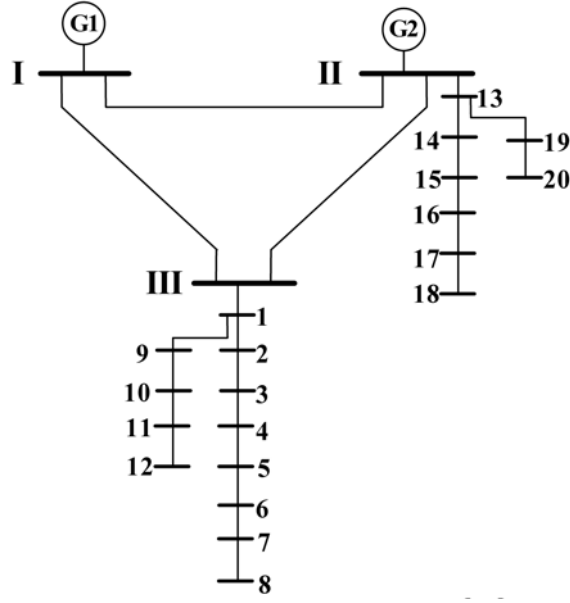


Figure 4.9: The test system

## 4.6 Numerical simulation

This section provides a simple case study to demonstrate the effectiveness of the proposed agent-based DRX market clearing mechanism. Specifically we aim to examine the following aspects which arise from the above analysis.

1. The optimality of agent-based market clearing.
2. The convergence of classical and Newton price tâtonnement methods.
3. The effects of core market parameters on the price convergence.

### 4.6.1 Test system

For simplicity, we consider the test system introduced in previous chapter. It consists of both transmission and distribution networks operated by a Transco and a Disco, respectively. There is also one Reco and one ESCo—each deals with all customers. For clarity, the system is shown again by Fig. 4.9.

For the ESCo and its customers we assume a *strictly convex* cost of producing DR given as follows:

$$C_i = \sum_{l \in \mathcal{L}_i} (a_i x_{i,l}^2 + b_i (1 - \theta_{i,l}) x_{i,l}) \quad (4.22)$$

where  $i = \text{ESCo}$ , and  $l = 1, 2, \dots, 20$ . The coefficient  $\theta_{i,l}$  is called the “customer type” and takes a value between 0 and 1.  $\theta_{i,l}$  represents a customer’s willingness to curtail load to provide DR. As  $\theta_{i,l}$  increases, DR cost decreases because the customer is more willing to

participate. In addition to  $\theta_{i,l}$ ,  $a_i$  and  $b_i$  are common coefficients applied to all customers. Values for these parameters are all given in [80, Table VII] [and also in previous chapter].

For each buyer  $j \in \{\text{Reco}, \text{Transco}, \text{Disco}\}$  we assume a *strictly concave* gross benefit derived from DR, given as follows:

$$B_j = \sum_{n \in \mathcal{N}_j} (-\alpha_{j,n} y_{j,n}^2 + \beta_{j,n} y_{j,n}) \quad (4.23)$$

where  $\mathcal{N}_j$  is the set of customer groups associated with buyer  $j$ . For example, in the case of the Transco,  $\mathcal{N}_{\text{Transco}}$  include two groups—one contains customers  $l = 1, 2, \dots, 12$  while the other contains  $l = 13, 14, \dots, 20$ . Customer groupings for other buyers, such as the Disco and the Reco, are all given in [80, Table II] [and also in previous chapter].

Both  $\alpha_{j,n}$  and  $\beta_{j,n}$  are valuation coefficients assigned to customer group  $n$  under buyer  $j$ . These coefficients reflect how much DR provided by the group as a whole is worth for the buyer. Detailed explanations of these coefficients and their assumed data values are given in previous chapter.

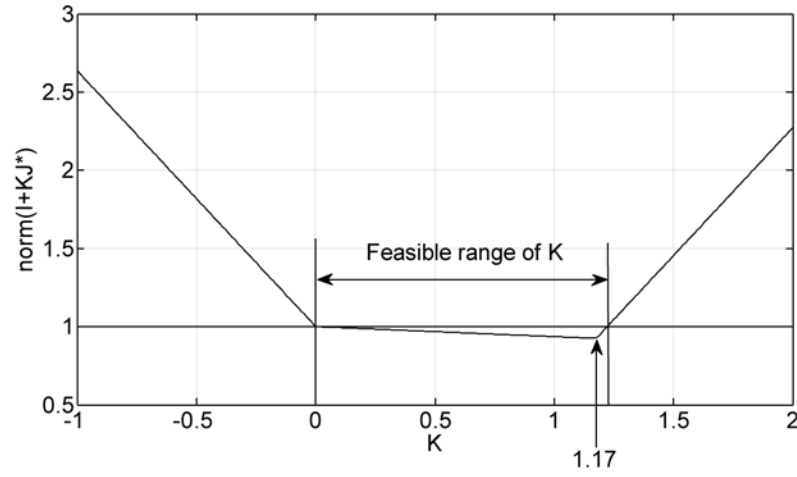
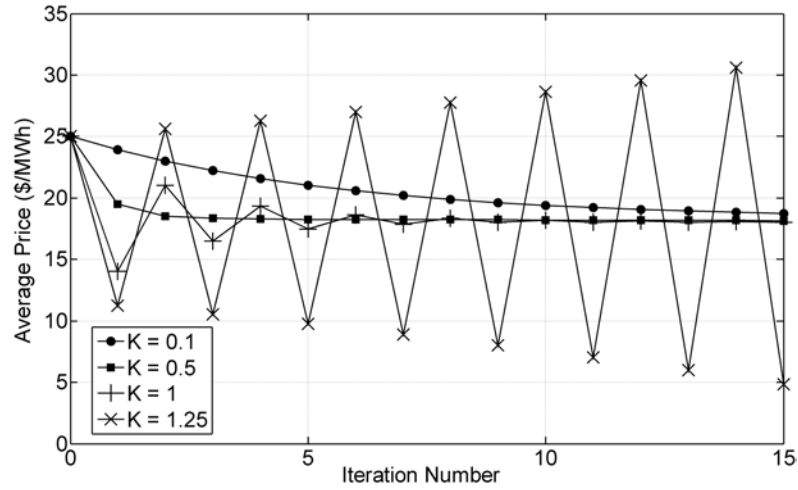
#### 4.6.2 Analysis of the market clearing results

This subsection presents a numerical study to substantiate the claim that the proposed DRX market clearing mechanism reaches Pareto optimality. The study compares the outcome of the proposed mechanism with the outcome obtained by directly solving the theoretical Pareto-optimal model (4.4)–(4.5), assuming the availability of cost and benefit data collected from agents. Note that the Pareto model cannot be implemented as the agents may be unwilling to share their private information.

Table 4.3: Comparative results

Market clearing	Total market surplus (\$)	Total quantity (MWh)	Average price (\$/MWh)
Theoretical model (Pareto optimality)	2124.1	32.2	17.9
Proposed scheme with Classical tâtonnements	2124.1	32.2	17.9
Proposed scheme with Newton tâtonnements	2124.1	32.2	17.9

The Pareto model is solved using the nonlinear programming tool GAMS/MINOS, while the proposed mechanism is simulated using MATLAB with the algorithm shown in Fig. 4.6. Both simulations employ the same data inputs and are assumed to be within a single hour. Comparative results are given in Table 4.3. For simplicity, only the total


 Figure 4.10: The convergence rate  $\|\mathbf{I} + \mathbf{K}\mathbf{J}^*\|$  versus the adjustment factor  $K$ 

 Figure 4.11: Classical tâtonnement for different  $K$ .

market surplus (calculated by (4.4)), the total DR quantity, and the DR price averaged over all buyers ( $(\sum_j \sum_n p_{j,n})/(\sum_j N_j)$ ) are shown in Table 4.3.

As can be seen, results for the proposed mechanism using either classical or Newton tâtonnements are identical to those of the theoretical model. The total market surplus is \$2124.1 which is also the global optimal value. At the same time, the total quantity and the average price are 32.2MWh and 17.9\$/MWh, respectively. These outcomes constitute a competitive market equilibrium. The results confirm that the proposed mechanism has reached the point of Pareto optimality.

### 4.6.3 Convergence assessment

This subsection illustrates the developed conditions (4.18) and (4.20) that are required for price convergence using classical and Newton methods.

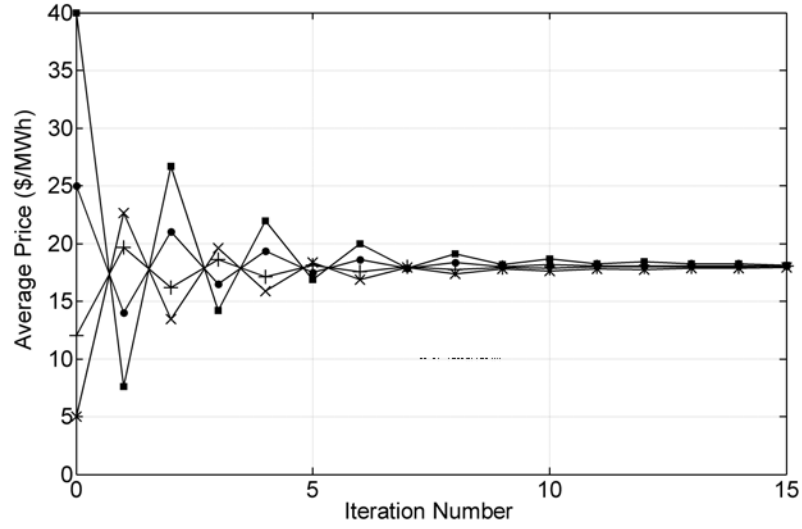


Figure 4.12: Convergence of the classical tâtonnement with different starting points

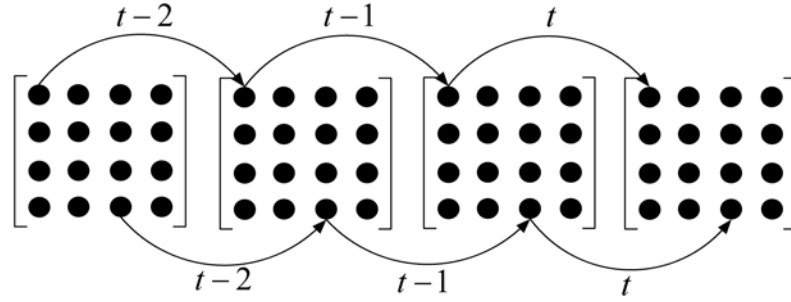


Figure 4.13: Illustrating the online estimation of inverse Jacobian matrix

For classical tâtonnement, the convergence rate is given by  $\|\mathbf{I} + \mathbf{KJ}^*\|$  which depends on the price adjustment factor  $K$ . As can be seen from Fig. 4.10, when  $K$  is either less than 0 or greater than 1.2,  $\|\mathbf{I} + \mathbf{KJ}^*\|$  is greater than 1. This consequently causes the price to diverge from its equilibrium point, as illustrated by Fig. 4.11. For illustrative purposes, only 15 iterations are shown here. In fact, the convergence to the same equilibrium point for  $K = 0.1$  occurs at iteration 30.

It can also be observed that as  $K$  is larger within its *feasible range* (i.e.,  $(0, 1.2]$ ),  $\|\mathbf{I} + \mathbf{KJ}^*\|$  becomes smaller, thus making the price converge more quickly. However, when  $K$  is near to 1.2,  $\|\mathbf{I} + \mathbf{KJ}^*\|$  increases significantly, which reduces the convergence speed. Therefore,  $K = 1.17$  appears to be the best choice in this example.

Fig. 4.12 shows the impact of selecting initial price  $\mathbf{p}_0$  on the convergence of classical tâtonnement ( $K = 1$ ). As can be seen, different values of  $\mathbf{p}_0$  lead to the same equilibrium solution that is unique in the DRX market. However, the cases with  $\mathbf{p}_0 = 40\$/\text{MWh}$  or  $\mathbf{p}_0 = 5\$/\text{MWh}$  that are relatively far from the equilibrium point ( $17.9\$/\text{MWh}$ ) use over

15 iterations to converge, which is slower than cases that require only around 10 iterations for the convergence.

For the Newton tâtonnement, the convergence rate is given by  $(L \cdot \max \{ \|\Delta^t\| \} + M \cdot \|\mathbf{e}^0\|)$  that depends on error  $\Delta^t$  in estimating the inverse Jacobian matrix  $(\mathbf{J}^t)^{-1}$  under a given price initiation. This *online* estimation is described in Fig. 4.13, where each individual element (given by  $\bullet$ ) of  $(\mathbf{J}^t)^{-1}$  forms a “time series” along successive iterations  $t$ . Estimating  $(\mathbf{J}^t)^{-1}$  entails determining all time-series elements in parallel.

Fig. 4.14 presents the impact of inaccurate online estimation on the convergence of the proposed Newton method. Impact is simulated by assuming different ranges of estimation error in percentage,  $(\|\Delta^t\|/\|(\mathbf{J}^t)^{-1}\|) \cdot 100\%$ . (Within a given range the error is selected at random for each iteration  $t$ , and then added to the time series given above). The graph shows that when the percentage error is relatively small (i.e., less than 10%), the price converges quickly to its equilibrium solution. However when the error is as large as 90%-120%, the price fluctuates. In this case, there is a very high chance the Newton method will not converge. This result underlines the importance of estimating reasonably the Jacobian matrix online to achieve a robust solution convergence.

Here we illustrate a simple and practical method for the online estimation. This method computes each element of  $\mathbf{J}^t$  (i.e.,  $\partial z_{j,n}^t / \partial p_{j',n'}^t$ ) using the principle of “finite difference” in time series [108]. That is,  $\partial z_{j,n}^t / \partial p_{j',n'}^t \approx (z_{j,n}^t - z_{j,n}^{t-1}) / (p_{j',n'}^t - p_{j',n'}^{t-1})$ , where all exact values of  $z_{j,n}^t$ ,  $z_{j,n}^{t-1}$ ,  $p_{j',n'}^t$ , and  $p_{j',n'}^{t-1}$  are known to the market operator via the clearing process given above. Consequently, no private cost and benefit information from an agent is required.

Fig. 4.15 shows simulation results using the finite-difference method. As can be seen, the Newton tâtonnement converges quickly to the same (unique) equilibrium solution for different starting points. This performance can be explained by the relatively low error in  $\mathbf{J}^t$  estimation (i.e., less than 10% for any  $t > 1$ ). It is also observed that the maximum number of iterations required for the convergence is only 6 which is faster than most classical tâtonnement cases shown in Fig. 4.12.

#### 4.6.4 Discussion

The proposed DRX market clearing mechanism follows the notion of a competitive market as was defined by general equilibrium theory in microeconomics. In particular, it seeks to explain the competitive behavior of buying and selling agents in a DRX market, and then proving that equilibrium prices for all DR quantities can be achieved via a tâtonnement process under such agent behavior.

The theoretical work developed in this paper should be regarded as an extension of those presented in microeconomics. In fact, general equilibrium theory [75] focuses inten-

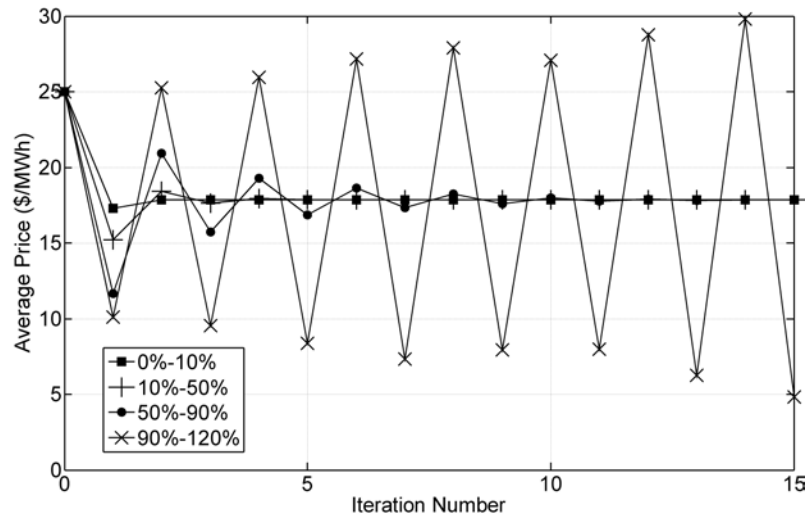
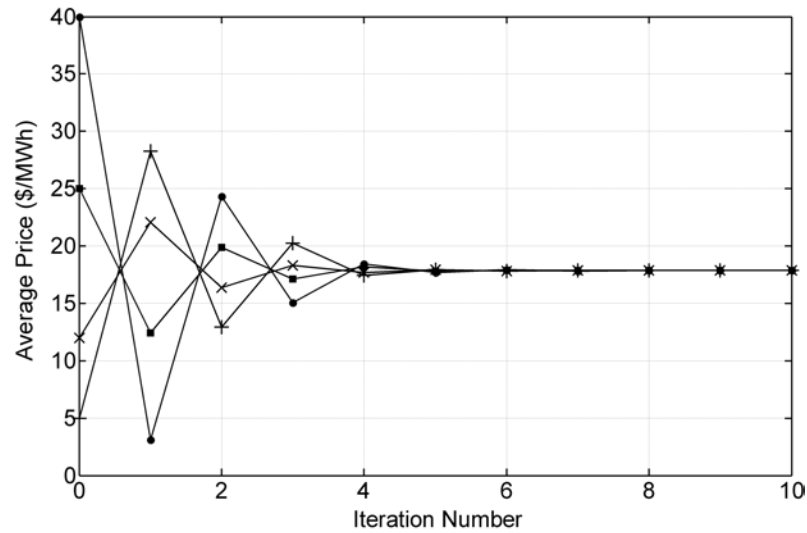


Figure 4.14: Newton tâtonnement with various ranges of estimation error


 Figure 4.15: Newton tâtonnement via finite-difference online estimation of  $\mathbf{J}^t$ 

sively on the treatment of markets for private goods. To the best of our knowledge, very little attention has been paid to developing a similar (complete) theory for competitive trading of public goods (such as national defense, fresh air, common lands, rivers, etc). This lack of attention is explained by the fact that provision of most of these goods are usually under a government control through the use of taxation. Consequently, a competitive negotiation scheme for rights to use these goods does not appear to be practical.

However, DR as a form of public goods is different. The provision of DR is *not* subject to government intervention. In fact, DR can be produced by any customer whenever they are paid to do so. Also, DR can be supplied to any buying agents (Recos, Transcos, Discos)

whenever they need it and are willing to pay. In this sense, developing a competitive market for the trading of DR as public goods is both feasible and necessary.

Based on this review of general equilibrium theory, we suggest that our DRX proposal for a public good market clearing mechanism, using either classical or Newton price tâtonnement methods, makes a sound contribution to the field of microeconomics. We also believe that the theoretical framework developed in this paper for competitive trading of DR can also be applied to trading other public goods, as long as they are not under government control. In fact, the framework is generic in the sense that it involves multiple buyers, multiple sellers, and multiple products or quantities (i.e., an “exchange economy”). Note also that the framework did not make any assumptions beyond those common in microeconomics, such as the “preference convexity” made for proving the existence and the uniqueness of market equilibrium.

## 4.7 Summary

This chapter presented the design and evaluation of an agent-based market clearing scheme for the eXchange of Demand Response. The proposed scheme uses Walrasian auctions, where participating agents update their quantity bids in response to prices adjusted by the market operator. This auction is repeated iteratively until the market equilibrium is obtained at a point where the market outcome is Pareto optimal. Both the existence and the uniqueness of this equilibrium are proven under the condition that agent preferences are strictly convex.

The price adjustment is performed using either classical or Newton tâtonnements. Both methods have advantages and limitations. Although classical tâtonnement is easy to implement, it may not converge to an equilibrium solution if the value of price adjustment factor  $K$  is not suitably chosen (i.e., within its feasible range). On the other hand, the Newton method offers robust convergence, although in return it requires greater computational effort in estimating the Jacobian matrix online. This estimation is performed using the finite-difference principle.

## Chapter 5

# Cost–Benefit Analysis and Treatment of Externalities

### 5.1 Overview

This chapter proposes a comprehensive framework for assessing short-term financial costs and benefits derived from scheduling DR using various market-clearing schemes, including the conventional partial schemes and the DRX introduced in previous chapters. Throughout the framework development, we analyse DR cost and benefit for each participant in a DR(X) market, as well as for Gencos and Recos in the wholesale electricity market. Based on these local analyses, a global evaluation is performed to determine whether the optimised DR can give a positive social surplus. If so, the DR will be dispatched during the time period (i.e., an hour) under consideration. The proposed cost–benefit assessment framework is illustrated on a small power system, and its usefulness reported through the demonstration of externalities across all involved parties. Case studies on the Roy Billinton Test System (RBTS) are given to examine the scalability of the proposed framework.

One of the main motivations for developing this framework is to establish a *rigorous* evaluation of DRX as the key innovation proposed this thesis. Here the evaluation relies on only a few justifiable and, in fact, justified assumptions which demonstrate the validity of the market outcome including DR costs and benefits derived from a DRX clearing scheme. In addition to this, the framework can be used to evaluate certain classes of conventional DR schemes such as the Transco-based, the Reco-based, and the Disco-based. This substantiates the applicability of the proposed assessment framework.

The chapter is structured as follows. Section 5.2 introduces methodologies commonly used for an economic assessment. Based in these standard methods, the overall structure of the proposed framework for evaluating DR costs and benefits are described in Section 5.3, with the details given in subsequent sections, 5.4 and 5.5. The developed framework is illustrated via a small-scale study in Section 5.6, and then its scalability is examined in Section 5.7 using the RBTS. Concluding remarks are finally given in Section 5.8.



## 5.2 Common economic assessment methodologies

### 5.2.1 Cost–benefit analysis

Cost–benefit analysis, sometimes called benefit–cost analysis, is an important approach to evaluate the economic efficiency of decision making by a rational business firm. Formally it refers to the process of estimating both costs and benefits derived from various decision alternatives, and then the best alternative offering highest “net value” (i.e., equal to the benefit less the cost) will be chosen by the firm as the final decision [109]. There are several classes of cost–benefit analysis, based on which time scale of the economic decision to be made (see Table 5.1).

Table 5.1: Examples of cost–benefit analysis

Time scales	Examples
Long term	Investment raking, proposal examination, and policy evaluation, etc
Medium term	Project management, engineering design, and resource planning, etc
Short term	Resource scheduling, bidding strategies, and market clearing, etc

Long–term (several years) cost–benefit analysis is often used for assessing the economic efficiency of an investment in term of its invested money and the expected return. If the latter can sufficiently offset the former, the investment is said to be profitable and will certainly be chosen by the firm. Electricity network reinforcement is a good example of invesment via cost–benefit analysis, in which the cost is an amount to be spent on buying new equipment (such as generating units, transmission lines, transformers) to upgrade the existing networks, and the benefit is an improvement in network reliability and security as a result of new capacity installed. In addition to the investments, long term cost–benefit analysis can be applied toward examining business proposal that is a written offer from a supplier to a prospective user. Here the user need to determine whether the long–term value of the underlying product being offered can be higher than its price paid to the supplier. Besides the proposals, the task of evaluating new government policies also entails using a cost–benefit analysis which empirically estimates the long-term (social) outcomes derived from these policies, as well as their implementation costs. For example, to establish the Renewable Energy Target (RET) policy that 20% of Australia’s electricity must be produced from renewable energy sources by 2020 [110], the government carefully analysed the trade-off between environmental benefits (i.e., via reduction in carbon emission) and the costs of replacing conventional sources (such as coal and nuclear) by the renewable.

In the medium term (i.e., several months up to one year), cost–benefit analysis can be used for project management involving planning, organizing, and securing the utilization of resources to achieve specific goals. Assessing the project’s effectiveness entails determining whether such goals can be obtained under certain constraints, including available resources (i.e., labor, budget), time required to complete, and the project’s scope (for instance, what must be done to produce the end results). If all constraints are met, the project is said to be sustainable [111]. A similar situation is applied to the context of engineering design that is the formulation of a workable scheme to assist with the engineers in creating a product. Besides the underlying scientific and technological details, an engineering design should account for several important economic factors including the implementation costs as well as the commercialization benefits. In fact, trade-off between these factors determines the design outcome [112].

Short-term cost–benefit analysis, which is the main focus of this chapter, refers to a process of assessing the economic impact of making a decision relating to a relatively short period of time, ranging from days through hours down to minutes. Such an evaluation methodology is often used, for instance, in the resource management by a firm, in which the underlying resources (such as money, human labor) is scheduled in terms of location (i.e., where to be allocated?) and quantity (i.e., how much to be allocated?), for the purpose of maximizing the net value resulting from the resources utilization as a whole. This value can be calculated by taking into account both the total cost of purchasing these resources and the total benefit derived from them.

This chapter utilizes the short term cost–benefit approach to develop a comprehensive framework for evaluating DR as an important resource provided by ESCos (on behalf of electricity customers) and used by Transcos, Recos, and Discos. For the ESCos as a firm, DR cost is the compensation to customers for their load curtailments, while the benefit includes revenues collected from DR users. For each of these users, DR cost is the payment to ESCos who provide DR resource, and the benefit is associated with the risk management (i.e., to improve network reliability by the Transco and Discos, or to mitigate spot price spikes by the Recos) using DR. Note that the cost–benefit analysis here is performed at the *individual* level (i.e., for each DR provider and user as a firm) rather than at an aggregated level (i.e., for the whole power system).

### 5.2.2 Externality evaluation with public goods

As a cost–benefit analysis deals with the decision making by an individual firm only, there should be another method for assessing the overall economic efficiency. Such a method is important because it reveals a practical issue associated with the fairness across all firms, the externality. Formally externality refers to a present whenever decisions made by some

firms directly affect the well being (either costs or benefits) of others [75]. A cost in this case is called external cost, while a benefit termed external benefit. For example, the air pollution resulting from burning fossil fuels to produce electrical energy is an external cost, because it causes damages to non-energy businesses such as crops or public health care. Similarly a nation's use of military has an external benefit as it favor every citizen including those who do not participant in the military force. Additional examples of externality are given in Table 5.2.

Table 5.2: Examples of externality

Types	Examples
Negative externality (with external costs)	Air pollution, anthropogenic climate change, nuclear waste from nuclear plants, etc
Positive externality (with external benefits)	National defense, education, knowledge spillover, etc

The externality issue is often associated with the scheduling of a public good. As was defined in Chapters III and IV, public good is a special type of resources with each single resource unit consumed by multiple firms. For example, national defense given by Table 5.2 is clearly a public good since it is utilized by every citizen living within the country. Due to this utilization, whenever a firm produces a public good, others can automatically benefit from it. This external benefit can make the public good production and allocation unfair among firms, if there is no proper scheduling mechanism [79]. Table 5.3 shows the difference between public goods and private goods (the latter is generally the goods not to be jointly consumed.)

Table 5.3: Private goods versus public goods

Types	Examples	Properties
Public goods	national defense, fresh air free-to-air television, etc	Non-excludable, non-rivalrous.
Private goods	food, clothes, cars, personal electronics, etc	Excludable, rivalrous.

As can be seen, the underlying properties of a public good, making it different from private goods, are non-excludability and non-rivalry. The former means that it is impossible by nature to prevent people from having access to the good. For example, excluding any citizen living within a country from the benefit of national defense is insuperably difficult, because the fundamental purpose of such a defense is to protect all citizens from being attacked. Non-rivalry, on the other hand, means that each firm's consumption of a

public good leads to *no* subtractions from any other firm's consumption of the good [113]. National defense can also be considered here as an example of the non-rival property.

The public good's non-excludability and non-rivalry often lead to a free-riding problem in which some people take advantage of the good without contributing anything towards its production. For example, some people may avoid participating in the army but still enjoy the common benefit of national defense [113]. Such a free-riding issue can be explained by the human nature, that is, regardless of how much others contribute for the public good, a "self-interested" person is better off not contributing [75, 79]. In the worst case where nobody contributes, the good would not be supplied and the market is said to fail.

The notion of externality followed by public good with a free-riding problem constitute a common methodology for assessing the economic efficiency of market mechanisms and government policies that involves the allocation of a public good among firms. For example, the government often uses such a method for evaluating the taxation policy that facilitates the development of a national defense system. The evaluation aims to determine whether every citizen pays appropriate tax according to the benefits they gain from that system. If there is evidence of the free-riding problem where certain people have an opportunity to evade taxes, the policy needs to be revised [113].

This chapter utilizes the concepts of externality, public good and free rider to develop a comprehensive framework for assessing the economic efficiency of the existing DR scheduling schemes. The underlying principle behind this development is that DR is considered a public good in the sense that multiple beneficiaries (a Transco, a Reco, and a Disco) can jointly "consume" a given DR quantity (i.e., a load reduction) provided an ESCo on behalf of an electricity customer. This arrangement can be explained by the customer's involvement with all these beneficiaries, as discussed in previous chapters. In fact, it can be easily shown that DR has both non-excludable and non-rival properties mentioned above [80].

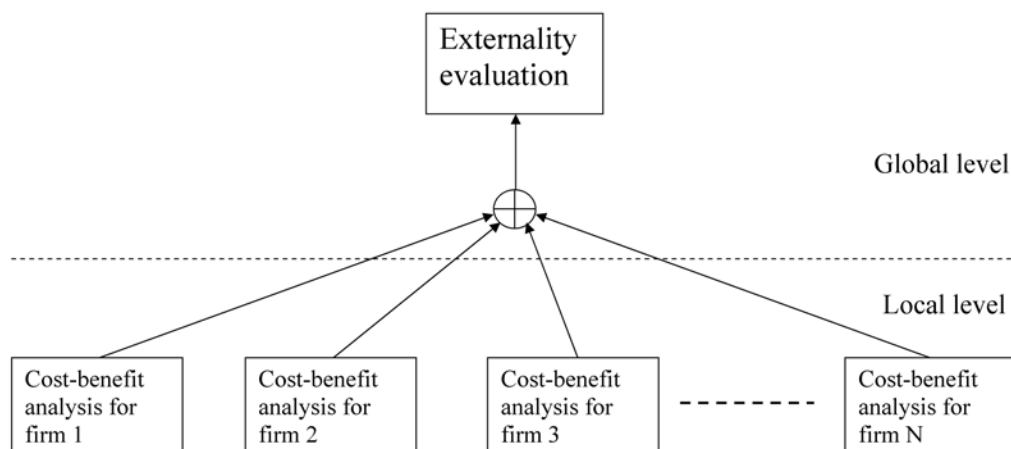


Figure 5.1: The whole assessment procedure

We conclude this methodological section by showing the whole assessment procedure on Fig. 5.1. Here the global externality evaluation across all players relies on the localized cost–benefit analysis for each firm (i.e., Transcos, Recos, and Discos). Such a “bottom-up” approach is central to developing a comprehensive assessment framework in the subsequent sections.

### 5.3 A novel framework for assessing financial DR benefits

A prerequisite for the development of a comprehensive framework to assess the financial DR costs and benefits across all stakeholders is that, the framework must be incorporated with the existing operational schemes that have been implemented, or is currently considered, for scheduling DR in real markets. Such existing schemes can be classified into three broad categories [64, 80], whose trends are quickly reviewed in the following subsection and are then used as a basis for developing the cost—benefit assessment framework.

#### 5.3.1 Trends in developing DR scheduling schemes

##### Transco-based models

This class of DR-scheduling schemes is operated by Transcos which are primarily responsible for managing power system security at a transmission level [85]. Such Transcos are not involved directly in energy supply markets and their roles in generation scheduling will be limited to ensuring that the submitted schedules are feasible [12]. At the other end of the scale, an Independent System Operator (ISO) has (i.e., in the U.S. context) a wide range of responsibilities, for instance, day-ahead security-constrained energy supply market clearing. For simplicity, this chapter only considers the role of a Transco.

Within a Transco-based scheme, customers provide DR as a resource in the form of load reductions to balance the active power generation and demand on a given timescale (e.g. hour-ahead), consequently ensuring transmission network security. Examples of the Transco-based scheme can be found in [40, 49, 80, 85, 87, 88]. Traditionally DR has been provided under strict conditions such that the Transco is allowed to curtail loads of any customer (given that these curtailments improve network security) and then compensate these customers with a fixed fee [88]. Many competitive approaches for DR procurement have been proposed during the last twenty years. Competition in supplying DR can be introduced by using either interruptibility contracts between the Transco and customers, or some type of organized market-based scheme [87]. Under contract arrangements, each customer negotiates DR with the Transco on a monthly or yearly basis. In a market-based scheme, all customers independently offer their own DR as a physical capacity (MWh) to a spot market on a daily or hourly basis, in which the Transco clears these offers by

optimizing the total benefit for all involved parties. The offered capacity can be “called” by the Transco requesting customers to curtail their load during peak demands.

The market-clearing approach has been given more attention than the contract approach in recent years. In fact, some power utilities in Australia, the U.S., and Europe have implemented dedicated spot markets for trading DR capacity [87,88]. These markets can achieve economic efficiency as competitive prices are taken into account when selecting customers to supply DR.

Some recent studies have proposed a small extension of the Transco-based market-clearing scheme [40, 49, 80]. In these studies, a price-quantity demand curve is used to represent prices at which the Transco is willing to buy DR of the corresponding quantities. This demand curve is derived from the valuation of DR (how much the DR is worth for the Transco and how much the Transco has to pay for it). Under this arrangement the demand curve is matched with the corresponding supply curves offered by the customers. The clearing of this market will result in both a quantity and a price of DR to be scheduled in the power system for a given hour. From a theoretical viewpoint, this approach, which is based on a well-known demand-supply model in microeconomics, inherits many advantages of the model compared to conventional DR approaches [75]. For example, the economic efficiency of DR scheduling is improved via demand-supply matching, while the network security criteria is fulfilled under the valuation of DR capacity leading to a demand curve.

### **Disco-based models**

This category of DR schemes is related to Discos operating a local distribution network consisted of many radial feeders connecting directly with the customer loads. As with the Transco, Discos benefit from DR by using it to enhance distribution network security. Examples of a Disco-based scheme can be found in [80, 86–88]. In this scheme, Discos directly schedule and pay for the load curtailments as a callable capacity physically offered by their customers. The payment calculation is based on both Disco and customer benefits. The latter can be estimated by either surveying customers or using historical data [86].

### **Reco-based models**

The final category focuses on Recos, who provide contracts for selling electricity at given prices to small customers. Examples of Reco-based DR-scheduling scheme can be found in [80, 87–90]. Within this scheme, customers submit DR capacity offers specifying the financial incentives at which they are willing to reduce loads for providing DR. The Reco then clears these offers, aiming to maximize profits for both customers and the Reco itself [90]. Profit for customers is a compensation for load curtailment, while profit for the Reco is a possible reduction of risk caused by spot price spikes. The curtailment compensation could be either change of retail price or an amount of reward that is unrelated to that price. The former is considered to be beyond the scope this chapter.

## DRX models

DRX is the most important proposal given by this thesis and is quickly explained here for clarify. Informally speaking, DRX is considered a generalization of the above-mention Reco-based, Transco-based and Disco-based models, in which the former incorporates DR benefits for all players within a comprehensive DR scheduling scheme, while the latter (models) considers only a subset of these benefits. Formally DRX is a new and separate market where DR in the form of hourly load reduction is treated as a public good to be exchanged between buyers and sellers. Buyers including Transco, Disco and Reco want DR for their risk management benefits (i.e., relating to network reliability or market volatility). DR sellers including the ESCos on behalf of electricity customers supply DR as a source of income.

In previous chapters we developed two different DRX market clearing schemes, namely agent-based and pool-based. These schemes, which are based on on microeconomic and optimization theory, are formalizations of the DRX concept from different market perspectives. While a pool-based market clearing scheme refers to centrally operating paradigm with resources pooling, the agent-based scheme relies mainly on agent local optimization in a decentralized manner. Definitely, each scheme has their own advantage and limitation which have been extensively discussed in previous chapters.

## Common trends

In these four scheduling categories, DR capacity in the form of (callable) load curtailment is treated as a market product traded between several involved parties. For instance, within a Reco-based scheme, DR from customers are offered to the Reco for mitigating spot price spikes. In this operating paradigm, a market clearing approach was developed for each category of DR capacity scheduling. Particularly, in a DRX, demand for the DR product is matched by its supply, with the aim to optimize the total market benefit.

The major difference between these scheduling categories is that, they consider various set of participants in the liberalized system [64]. For example, the Transco-based scheme involves only the Transco and electricity customers, while the Reco-based scheme deals with DR trading between the Reco and the customers. Such “partial” approaches could be inefficient because they do not incorporate the benefits and losses of other involved parties within the DR scheduling process. In the light of microeconomic theory, this inefficiency is characterised by the externality and free-riding issues as a direct consequence of scheduling DR as a public good. These issues are given in Table 5.4.

As can be seen, the externality issue occurs in all schemes but is fairly weak for the DRX due to the absence of free riders [80]. Here Gencos always suffer revenue loss resuting from the scheduled DR, i.e., reducing the electricity demand that the Gencos would otherwise sell to the Recos. This loss is the major source of externality in any DR scheduling schemes

Table 5.4: Characteristics of DR scheduling schemes

Scheduling schemes	Involved parties	Free riders	Sufferer	Externality
Transco-based	Transcos and customers	Discos, Recos	Gencos	Strong
Disco-based	Discos and customers	Transcos, Recos	Gencos	Strong
Reco-based	Recos and customers	Transcos, Disco	Gencos	Strong
DRX	Transcos, Discos, Recos and customers	None	Gencos	Fairly weak

including the DRX. In this regard, this chapter develops a comprehensive assessment framework, which critically analyses the externality limitation of each scheduling scheme and then suggests directions for future improvements. For the externality analysis, we will incorporate the following aspects within the proposed framework:

1. We assume that DR is (in any scheme) scheduled using an appropriate market clearing approach. This assumption is, in fact, realistic considering the current trends in DR scheduling given in the above categories (i.e., Transco-based, Disco-based, Reco-based). Note also that the proposed framework can be extended to account for a non-market-clearing approach to schedule DR.
2. We assess short-term DR benefits only (i.e., hour-ahead). Consideration of the long-term DR benefits including deferrals in both generation and network capacities is not considered here.
3. The assessment focuses on DR in the form of load reductions within a single period of time (i.e., one hour), which is still rich for the externality demonstration. The load recovery effect following a reduction is considered as future work.
4. The framework is to be developed in a *rigorous* manner with a limited set of justifiable assumptions. Although some important ideas for this development first appeared in previous chapters, they are not yet verified and consequently need to be re-considered here.

### 5.3.2 Proposed framework

It is difficult to develop a common framework to be used for assessing benefits under all above categories of DR schemes. Thus, each category should be adapted by a suitable framework that is slightly different from those for other categories.

The assessment framework for a Transco-based market-clearing scheme described above is given in Fig. 5.2. As can be seen, the framework analyses a given time period  $T$  which coincides with the generation dispatch interval (i.e., hour-ahead) in the electricity trading market—making the framework synchronized with the pre-existing economic operation of a



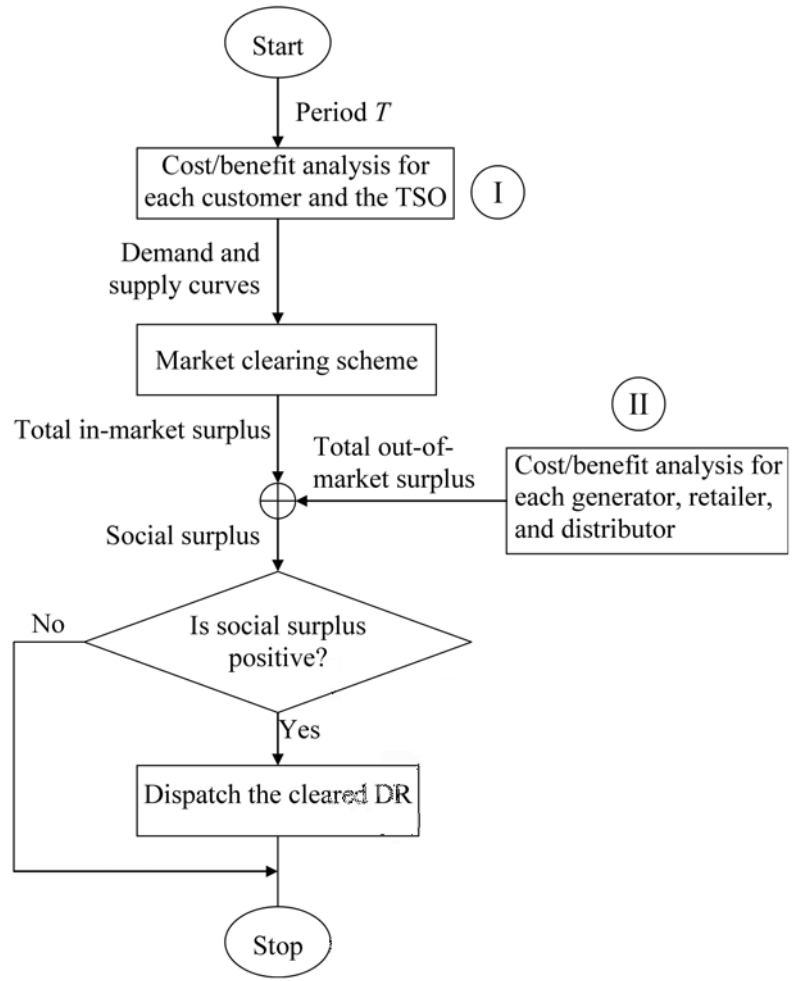


Figure 5.2: Flow chart of the framework for assessing DR costs and benefits

power system. Within period  $T$ , the framework performs two major assessment steps which are both based on a standard cost/benefit analysis technique [109]. These steps are called *in-market* and *out-of-market*, respectively. The former deals with parties participating in the DR market (such as the Transco and customers), while the latter deals with parties who are not directly involved in the market (such as Recos, Gencos and Discos). The benefit for each market participant is considered as in-market as it results from negotiating DR within the market. There are some additional benefits to Recos, Gencos, and Discos created from reducing the spot price spikes and improving the distribution network reliability, which are not taken into account in an ISO-based market-clearing process. Consequently, these benefits are considered to be free, as the out-of-market parties do not have to pay for them. Only the Transco, on behalf of transmission network users, buys DR for improving the transmission network reliability under the given scheme, while non-paying beneficiaries are referred as free riders.

This framework can be modified to assess the benefits under other classes of DR-scheduling schemes. For example, by exchanging the roles between Transco and Disco in managing DR, the former becomes an out-of-market player which is put into block II of the framework given by Fig. 5.2, while the latter is now an in-market player put into block I. Such a modified framework can then be used to evaluate Disco-based DR benefits. Similarly, putting the Reco into block I and moving the Transco to block II results in a Reco-based assessment method. In the case of a DRX, block I includes customers, Transco, Reco, and Disco, while block II contains Gencos only. If all players were to participate in the process of DR scheduling (i.e., via market clearing), block II would be removed. This case is, however, rare and thus beyond the scope of this chapter.

The proposed framework utilizes both cost-benefit analysis and externality evaluation methodologies described above (i.e., see Fig. 5.1). The former, which is performed at a local level (i.e., for each firm), resides within blocks I and II of the proposed assessment framework. Externality, on the other hand, is examined at the global level considering the scheduling impact on the social surplus derived from DR.

Once the framework has been defined, a cost-benefit analysis for each involved party can be given. Sections 5.4 and 5.5, for illustrative purposes, consider the case of Transco-based DR scheduling. The other cases (i.e., Disco-based, Reco-based, and DRX) will be analysed in Sections 5.6 and 5.7.

## 5.4 In-market DR costs and benefits

### 5.4.1 Customers

Let us consider a customer  $l = 1, 2, \dots, L$  (where  $L$  the total number of customers). Its total benefit from both consuming electricity and supplying DR is given as follows:

$$B_l(x_l) = U_l(D_l^{\text{int}} - x_l) + c_l x_l - \pi_l^{\text{int}} \cdot (D_l^{\text{int}} - x_l) \quad (5.1)$$

where  $x_l$  is the quantity of DR to be supplied;  $c_l$  is the cost per MWh (that is marginal cost) to be paid to the customer for this quantity;  $U_l$  denotes customer's utility that is, by definition, a monetary measure of relative satisfaction over various electricity consumption levels [75]. This means  $U_l$  is a function of  $(D_l^{\text{int}} - x_l)$  where  $D_l^{\text{int}}$  is the electricity demand that the consumer intends to consume without curtailing load for DR;  $\pi_l^{\text{int}}$  is the retail electricity price.

Equation (5.1) states that the benefit  $B_l$  is equal to the sum of utility  $U_l$  and DR revenue  $c_l x_l$ , less the cost paid for electricity consumption. This equation follows a benefit-based approach to the cost-benefit analysis, in which the benefit has a priority over the cost [109]. There are two reasons for using this approach: 1) the electricity cost represents a minor fraction of total living cost for most consumers; 2) the electricity benefit is indis-

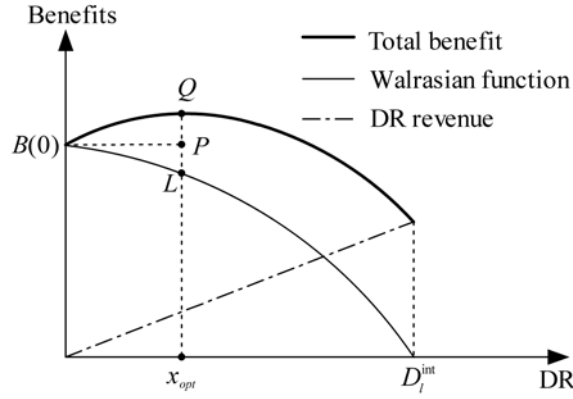


Figure 5.3: Benefits for consumer

pensible in their life [1]. Consequently, many consumers value the benefit much higher than the cost. Their consuming objective would be to maximize the former [114]. There may be some customers being more concerned about their electricity bills than the consumption benefits. In this case, their objective is to minimize the payment  $\pi_l^{\text{int}} \cdot (D_l^{\text{int}} - x_l) - c_l x_l$  for a certain level of utility  $U_l$ . Such customers, however, are not considered in this paper.

Now we examine the shape of the total benefit function  $B_l$  at given values of DR marginal cost  $c_l$ . At  $c_l = 0$ ,  $B_l$  resembles a *Walrasian function*, which is commonly used for demand studies [75]. As shown in Fig. 5.3, this function is: maximum at  $x_l = 0$ ; monotonically decreasing and concave for  $x_l \in (0, D_l^{\text{int}})$ ; zero at  $x_l = D_l^{\text{int}}$ . At  $c_l > 0$ ,  $B_l$  is the sum of Walrasian function and DR revenue. It slightly increases at small  $x_l$  because the rate of change in Walrasian function is near to zero which is outweighed by that of DR revenue. At relatively large  $x_l$  the concave shape of the Walrasian function indicates a rapid decline, causing the total benefit to decrease. Due to both the increases at small  $x_l$  and decreases at large  $x_l$ ,  $B_l$  must have a global maximum satisfying the following condition:

$$\frac{dB_l(x_l)}{dx_l} = 0 \quad (5.2)$$

To solve this condition, we determine the customer's utility  $U_l$  using the following.

**Proposition 5.4.1** *The utility at an arbitrary value  $x_l$  is calculated from a pre-specified initial level according to:*

$$U_l(D_l^{\text{int}} - x_l) = U_l(D_l^{\text{int}}) - \pi_l^{\text{int}} x_l \cdot \left(1 - \frac{x_l}{2D_l^{\text{int}} \epsilon_l}\right) \quad (5.3)$$

**Proof** Here we derive the utility function (5.3) that represents the *normal* consumption of customer  $l$  *without* being offered any DR incentive. By the definition of elasticity  $\epsilon_l$ ,

$$\begin{aligned}
\epsilon_l &= \frac{\Delta D_l / D_l^{\text{int}}}{\Delta \pi_l / \pi_l^{\text{int}}} = \frac{D_l - D_l^{\text{int}}}{D_l^{\text{int}}} \times \frac{\pi_l^{\text{int}}}{\pi_l - \pi_l^{\text{int}}} \\
\Rightarrow \pi_l &= \frac{\pi_l^{\text{int}}}{D_l^{\text{int}} \epsilon_l} (D_l - D_l^{\text{int}}) + \pi_l^{\text{int}} \\
\text{(a)} \therefore \int_{D_l^{\text{int}}}^{D_l} \pi_l dD_l &= \int_{D_l^{\text{int}}}^{D_l} \left( \frac{\pi_l^{\text{int}}}{D_l^{\text{int}} \epsilon_l} (D_l - D_l^{\text{int}}) + \pi_l^{\text{int}} \right) dD_l
\end{aligned}$$

On the other hand, assuming that customer  $l$  is a *price-taker*, then its consuming objective is given by

$$\text{(b)} \max \{U_l(D_l) - \pi_l D_l\} \Rightarrow \pi_l = \frac{dU_l}{dD_l}$$

We note that, in this particular optimization problem, the retail price  $\pi_l$  is treated as a *constant* because the consumption  $D_l$  by customer  $l$  (who is a price-taker) cannot alter such a price. Substituting (b) into (a), we obtain

$$\text{(c)} U_l(D_l) - U_l(D_l^{\text{int}}) = \frac{\pi_l^{\text{int}}}{2D_l^{\text{int}} \epsilon_l} (D_l - D_l^{\text{int}})^2 + \pi_l^{\text{int}} (D_l - D_l^{\text{int}})$$

Replacing  $D_l - D_l^{\text{int}}$  by  $-x_l$ , we complete the proof of (5.3). ■

Equation (5.3) states that  $U_l$  at any  $D_l^{\text{int}} - x_l$  where  $x_l > 0$  is equal to that at  $D_l^{\text{int}}$  minus a loss. The “loss” refers to consumer dissatisfaction due to load curtailments for providing DR. The utility loss can be calculated from consumer elasticity  $\epsilon_l$  as shown in (5.3). The “elasticity” refers to a measure describing the sensitivity of consumer demand (i.e., how much the demand deviates from its initial value) to a change in price. Such a measure implicitly reflects the *normal* consumption behaviour of a customer on a given timescale (i.e., hour-ahead) without any special incentive such as a DR reward.

By combining (5.1), (5.2), and (5.3), we imply (5.4) as a solution to total benefit maximization corresponding to a given marginal cost  $c_l$ :

$$x_l = -\frac{D_l^{\text{int}} \epsilon_l}{\pi_l^{\text{int}}} c_l \quad (5.4)$$

By rewriting this equation, we obtain a supply curve to be submitted by consumer  $l$  to the DR market:

$$c_l(x_l) = \frac{\pi_l^{\text{int}}}{D_l^{\text{int}} \cdot (-\epsilon_l)} x_l \quad (5.5)$$

We investigate this DR supply curve further using Fig. 5.4. First, since  $\epsilon_l < 0$ , this curve increases for any  $x_l > 0$ . This property implies that the customer will sell more DR if price increases. This selling behaviour is consistent with microeconomics [75]. Second, as given by formula (5.5), the supply curve is simple to the extent that it includes only a few input parameters (i.e., elasticity, retail price, and initial demand), for which the data can be easily obtained from real markets. With this modeling simplicity, however,

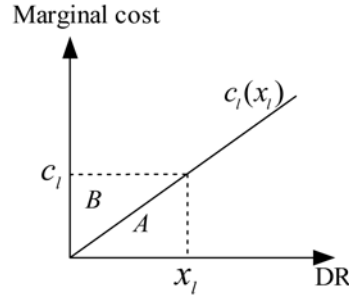


Figure 5.4: DR supply curve

one may wonder whether the formula (5.5) can realistically (or accurately) represent the actual value. We tackle this issue via the following

**Proposition 5.4.2** *The DR supply curve given by (5.5) represents true cost and net benefit of DR for the corresponding customer.*

**Proof** Tracing back to the original cost–benefit graph given by Fig. 5.3, the segment  $LP$  at the optimal point  $x_l$  represents a satisfaction loss due to load curtailment, while  $PQ$  represents a difference between optimal (total) benefit and the benefit obtained without load reduction (corresponding to  $x_l = 0$ ). This difference refers to a surplus (or net benefit) for the consumer who curtails load. The supply curve (5.5), on the other hand, is characterised by areas  $A$  and  $B$  (see Fig. 5.4). These areas are supposed (in microeconomic theory [75]) to represent DR cost and surplus associated with DR. To rigorously prove this representation that is also the content of Proposition 5.4.2, we need to show that  $A = LP$  and  $B = PQ$ . This task can be easily undertaken via some algerbric manipulation which is skipped here for simplicity.

**Remark** Proposition 5.4.2 indeed demonstrates the *validity* of the supply curve (5.5). Combining this proposition with the modeling simplicity given above, we see the “beauty” of (5.5) in terms of DR cost–benefit representation for a customer.

#### 5.4.2 The Transco

The Transco could significantly benefit from DR by using it to improve transmission network security including such factors as network congestion, and voltage and frequency stability during outages, most of which are difficult to value in financial terms. Then, an alternative valuation can be derived from cost savings due to improvements in each of these factors. Consequently we use a cost–based approach, rather than benefit–based, to analyse the DR cost–benefit for the Transco. This approach is illustrated in Fig. 5.5, in which the total cost is the sum of security costs plus the DR payment.

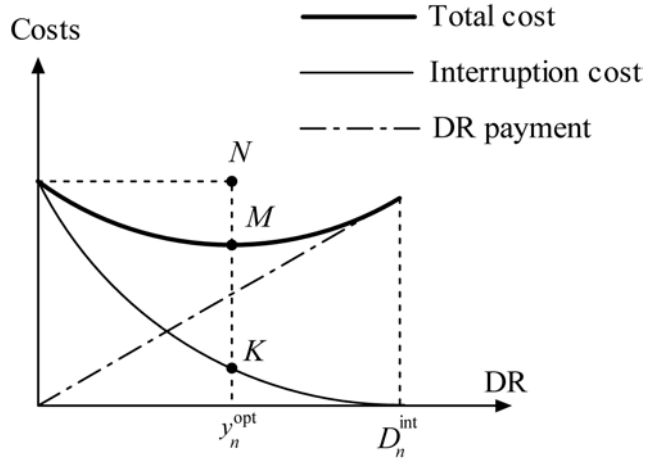


Figure 5.5: Costs to the Transco

For simplicity, here we consider only the interruption cost, which is incurred by electricity consumers due to involuntary load shedding during sudden outages and is usually taken into account by the Transco as part of its security cost. As shown in [82], other minor costs cannot affect the total (security) cost to a significant degree.

Now we analyse the cost graph shown in Fig. 5.5. As the DR quantity increases, electricity demand is reduced. Such a reduction can improve network security, as the network does not need to handle such a high level of power demand. This improvement reduces the cost of maintaining security within a pre-specified margin [82]. Thus, by *maximizing* the DR quantity, the security cost (or rather the interruption cost) will be minimized under a given set of other security actions (i.e., generation rescheduling, transformer tap changing, etc). However, DR incurs its own cost, which ideally should be kept at its *minimum*. Somewhere between these two local extremes, there must be a global optimum. Mathematically,

$$\min \left\{ VoLL.EENS + \sum_{n=1}^N p_n y_n \right\} \quad (5.6)$$

where each quantity  $y_n$  is aggregated load reduction using DR at bus  $n$  of the transmission network,  $p_n$  is price to be paid by the Transco for this quantity. *VoLL* (Value of Lost Load) is cost per MWh incurred by consumers due to involuntary load shedding. It is often used by the Transco as a proxy for measuring the negative security impact on consumers. For simplicity, we assume an average *VoLL* value for all consumers. Obviously, in reality, different consumers have different values of *VoLL*, which can be taken into account if required. *EENS* (Expected Energy Not Served) is the total amount of electricity demand to be interrupted as a direct consequence of sudden outages. Since these outages are treated as random events, *EENS* must be calculated using a stochastic transmission reliability assessment given as follows [83]:

$$EENS = T \sum_{k \in \mathcal{K}} P_k L_k^{\text{total}} \quad (5.7)$$

$$P_k = \prod_{e \in \mathcal{F}_k} \lambda_e \cdot \prod_{e \in \mathcal{S}_k} (1 - \lambda_e) \quad (5.8)$$

where  $\mathcal{K}$  is the set of credible outages occurring in a given time period  $T$ . For each outage  $k \in \mathcal{K}$ ,  $P_k$  is the probability of occurrence, while  $L_k^{\text{total}}$  denotes the total load to be shed during the outage. In practice,  $L_k^{\text{total}}$  is determined according to operational criteria defined by a Transco [49]. In this paper, it is given by the outcome of load shedding minimization under network security constraints (i.e., that is to avoid line overloading) [116, page 137].

Since each outage  $k$  includes faults of some equipment in the network (e.g., lines, transformers, generators, etc), and successful operations of other equipment, the outage probability  $P_k$  is the joint probability of all these failures and successes. This calculation is given by (5.8) [85], where  $\mathcal{F}_k$  and  $\mathcal{S}_k$  denote the set of faulted equipment and the set of correctly operating equipment, respectively. Additionally,  $\lambda_e$  denotes the failure rate of each piece of equipment  $e$ . Note also that  $\mathcal{F}_k \cap \mathcal{S}_k = \{\phi\}$ ,  $\mathcal{F}_k \cup \mathcal{S}_k = \{\text{all equipment in the network}\}$ .

In these  $EENS$  calculations, failure rates  $\lambda_e$  are assumed as constants and can be obtained by averaging historical failure data collected from the same network [115]. In reality, such failure rates depend on time-varying network conditions such as load demand. However, their exact values for every loading condition are cannot be determined [116]. Hence, the failure rates used in this paper are estimates based on historical data.

There is no direct means of incorporating the  $EENS$  calculations using (5.7)–(5.8) within the cost optimization problem (5.6) [76]. Therefore, an  $EENS$  estimating curve with respect to each variable DR quantity  $y_n$ , within time period  $T$ , must be derived using those calculations and then included in the objective function.

The experience of calculating  $EENS$  shows that the estimation curve would be *monotonically decreasing* and *convex* with respect to each quantity  $y_n$  [117] (see again Fig. 5.5a, where the  $EENS$  is considered to be proportional to the security cost by the factor  $1/VoLL$ ). In this case, we assume a quadratic  $EENS$  estimating curve

$$EENS = \sum_{n=1}^N (\alpha_n y_n^2 + \beta_n y_n) + \gamma \quad (5.9)$$

where  $\alpha_n$ ,  $\beta_n$ , and  $\gamma$  are locational coefficients to be determined from the set of calculated data points. Since  $EENS$  is convex,  $\alpha_n > 0$ . Also, since  $EENS$  decreases for positive  $y_n$ , its minimal vertex  $-\beta_n/(2\alpha_n)$  is positive,  $\beta_n < 0$ . In Sections 5.6 and 5.7, we will examine the accuracy of this estimation.

These coefficients reflect the sensitivity of  $EENS$  to a change of load at any bus. In other words, they attribute the benefit of load reduction at each location in the network.

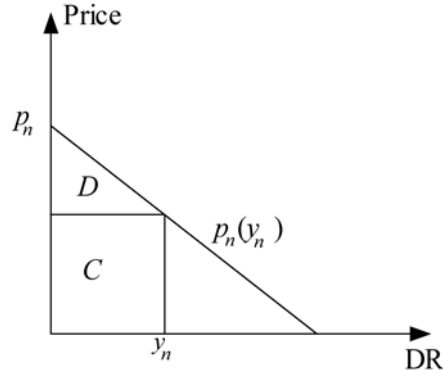


Figure 5.6: DR demand curve

Reducing loads at critical buses (that strongly affect the *EENS*) is likely more valuable than reducing loads at other buses.

With the estimated *EENS*, minimizing the cost function (5.6) yields a solution which represents a DR price–quantity demand curve to be used by the Transco for DR market clearing:

$$p_n = -VoLL.(2\alpha_n y_n + \beta_n) \quad \forall n = 1, 2, \dots, N \quad (5.10)$$

Now we examine the DR demand curve via Fig. 5.6. Since  $\alpha_n > 0$  and  $\beta_n < 0$ , the curve (5.10) is positive at  $y_n = 0$  and decreases for any  $y_n > 0$ . This property implies that the Transco will buy less DR if price increases. As with those for DR–selling customers, this buying behaviour of the Transco is consistent with microeconomic theory [75]. To further validate the demand curve, we present the following

**Proposition 5.4.3** *The DR demand curve given by (5.10) represents true cost and net benefit of DR for the Transco.*

**Proof** Tracing back to the cost graph given by Fig. 5.5, the segment *KM* at the optimal point  $y_n$  represents a DR payment made by the Transco to DR–providing customers, while *MN* represents a difference between minimal (total) security cost and the cost incurred without load reduction (corresponding to  $y_n = 0$ ). This difference is a surplus (or net benefit) for the Transco who is using DR for network security management. The demand curve (5.10), on the other hand, is defined by areas *C* and *D* (see Fig. 5.6). These areas are supposed (in microeconomic theory [75]) to represent DR payment and surplus derived from DR. To rigorously prove this representation which is also the content of Proposition 5.4.3, we would have to show that  $C = KM$  and  $D = MN$ . This task which can be easily undertaken via some algerbric manipulation is, again, skipped here for simplicity.

**Remark** Proposition 5.4.3 does not necessarily entirely demonstrate the validity of DR demand curve (5.10). In fact, this validity also depends on the accuracy of *EENS* es-



timisation using (5.9) (to be examined later), and more importantly, on the analysis of security costs incurred by the Transco. Since such an analysis takes into account interruption cost only, it cannot be fully realistic (i.e., excluding other minor security costs such as those for generation rescheduling during outages). Unfortunately considering all possible costs would result in the very complexity of the analysis, which ideally should be avoided. Hence, to make the cost analysis simple (i.e., for illustrative purposes), we do not mention all security aspects here. These can be considered in practice if required.

### 5.4.3 Market-clearing

With the demand curve calculated using a reliability assessment and supply curves collected from customers, the Transco would clear the DR market. As described above, this market clearing mechanism optimizes the economic efficiency created from the trading of DR subject to the demand-supply matching [75]. In particular,

$$\max \left\{ \sum_{n=1}^N \int_0^{y_n} p_n(y_n) dy_n - \sum_{l=1}^L \int_0^{x_l} c_l(x_l) dx_l \right\} \quad (5.11)$$

$$\text{s.t. } y_n = \sum_{l=1}^L u_l^n x_l \quad \forall n = 1, 2, \dots, N \quad (5.12)$$

The objective function (5.11) represents an in-market total surplus, which is equal to the gross benefit for the Transco less costs of producing DR by customers [75]. The former (which is depicted by area  $C + D$  in Fig. 5.5) is calculated by integrating the demand curve (5.10), while the latter (as it is depicted by the area  $A$  in Fig. 5.3) is calculated by integrating the corresponding supply curve, (5.5). These calculations are based on the above proofs of cost-benefit representations (i.e., Propositions 5.4.2 and 5.4.3). Note also that if the demand and supply curves do not reflect true costs and benefits for the corresponding market participants (the Transco and customers), the total surplus given by (5.11) would not be a true surplus but only a perceived one [75, 89].

The constraint (5.12) of this market clearing is the matching of demand and supply. In particular, each quantity  $y_n$ , which is demanded by the Transco at bus  $n$  of the transmission network, must be equal to the total quantity supplied by all customers located at that bus. Binary coefficient  $u_l^n$  represents the locational status of customer  $l$  to bus  $n$  ( $u_l^n$  is 1 if the customer is located at this bus, and 0 otherwise.) Note also that  $u_l^n$  remains a constant because the customer does not change its geographical location over a short time period (i.e.,  $T$ ). A more detailed description of  $u_l^n$  and its illustration can be found in previous chapters.

Clearing the market based on (5.11) and (5.12) will result in both a quantity and a price of DR to be dispatched. However, as indicated in Fig. 5.2, before the cleared DR is

dispatched, it is determined whether it will produce a positive social surplus. Under this assessment, out-of-market surplus is calculated and added to the in-market total surplus. This calculation is given below.

## 5.5 Out-of-market surpluses

### 5.5.1 Discos

The benefit of DR for a Disco is similar to the benefit for the Transco—an improvement in distribution network security resulting in a significant cost saving. The only difference between the two stakeholders is that, under the Transco-based scheme, the Disco is a free rider who gains the benefit of cost saving derived from DR without paying anything for it. Consequently DR surplus for the Disco is equal to this cost saving.

For simplicity, only the cost of power interruption caused by involuntary load shedding is considered here for the security cost analysis (in practice, other costs can be added if required). A reduction in this interruption cost can be calculated by assessing the distribution network security *with* and *without* DR provided by the corresponding electricity customers. In each case, the *EENS* is determined using a stochastic reliability assessment method applied at the distribution level of a power system [83, 116]. The cost saving (CS) is then defined as follows:

$$CS = (EENS_1 - EENS_0).VoLL \quad (5.13)$$

### 5.5.2 Recos and Gencos

The DR benefit for a Reco is the mitigation of spot price spikes during peak electricity demands [22]. Considering a Reco who offers supply contracts to each electricity consumer group  $g \in \mathcal{G}$  (consumers within each group have the same type of contract with a common retail price), the total profit  $P_R$  the Reco makes by buying bulk electricity on a spot market and selling this electricity to its customers is given as follows:

$$P_R = \sum_{g \in \mathcal{G}} (\pi_g^{\text{int}} - \rho) \cdot D_g \quad (5.14)$$

where  $\pi_g^{\text{int}}$  is a common retail electricity price offered to every customer within group  $g$ ;  $\rho$  is the electricity spot price (that is, for simplicity, assumed to be uniform among all customers);  $D_g$  is the aggregated electricity demand which group  $n$  (as a whole) purchases from the Reco. Then, the gross benefit derived from DR is

$$\sum_g (\pi_g^{\text{int}} - \rho_1) \cdot (D_g^{\text{int}} - y_g) - \sum_g (\pi_g^{\text{int}} - \rho_0) \cdot D_g^{\text{int}} \quad (5.15)$$

Here  $\rho_0$  is the spot price corresponding to the initial demand  $D_g^{\text{int}}$  without load reduction;  $\rho_1$  is the spot price at which DR has been dispatched; and  $y_g$  is the aggregated load

reduction from  $n$  (as a whole). Since the Reco in a Transco-based scheme does not pay anything, its surplus from DR is equal to the gross benefit given by (5.15).

Unlike the Disco and Reco who always enjoy benefits derived from DR, Gencos always suffer a financial loss caused by the same DR. This is due to the reduction in electricity demand that the Gencos would otherwise sell to Recos during the DR dispatch interval. In power system economics, this loss is referred as “lost scarcity rent”, given by [42]:

$$\left[ \rho_0 D_{\text{total}}^{\text{int}} - \int_0^{D_{\text{total}}^{\text{int}}} \rho(D_{\text{total}}) dD_{\text{total}} \right] - \left[ \rho_1 (D_{\text{total}}^{\text{int}} - y_{\text{total}}) - \int_0^{D_{\text{total}}^{\text{int}} - y_{\text{total}}} \rho(D_{\text{total}}) dD_{\text{total}} \right] \quad (5.16)$$

where  $D_{\text{total}}^{\text{int}}$ ,  $D_{\text{total}}$  and  $y_{\text{total}}$  is total initial demand, total actual demand, and total amount of load reduction, respectively, from all electricity customers together.

## 5.6 Numerical example

This section presents a simple study to illustrate how DR costs and benefits are evaluated using the proposed assessment framework under the Transco-based DR scheduling scheme and then under others such as Reco-based and Disco-based. Our particular focus is to demonstrate the existence of externalities among DR-involved parties, as a consequence of the free riding problem associated with DR as a public good.

### 5.6.1 Test system

Fig. 5.7 shows a small power system used for this case study. The system is comprehensive to the extent that it consists of both transmission and distribution networks which are operated by a Transco and a Disco, respectively. There is also one Reco and one ESc, each dealing with all customers. For simplicity, we assume that each customer represents a load point connected to the corresponding distribution feeder. Therefore, there are totally 30 customers in the system.

In the transmission network, all lines are assumed with a maximum power carrying capacity of 10MW, and failure rate ( $\lambda$ ) of 0.001/h. The two generating plants (i.e., G1 and G2) have maximum output capacities of 30MW and 10MW, and overall failure rates of 0.003/h and 0.002/h, respectively. Bus I is chosen to be the slack bus. The aggregated base loads connected to bus II, III, and IV are 5MW, 9MW, and 16MW, respectively.

In the distribution network, failure rate is assumed to be 0.001/h for each section, and all sections are of the same length. Also, all individual customer loads have the same value of 1MW. For simplicity, we also assume that all circuit breakers in the two networks are 100% reliable. That is, the breakers are opened immediately to isolate the faulty section from the network.

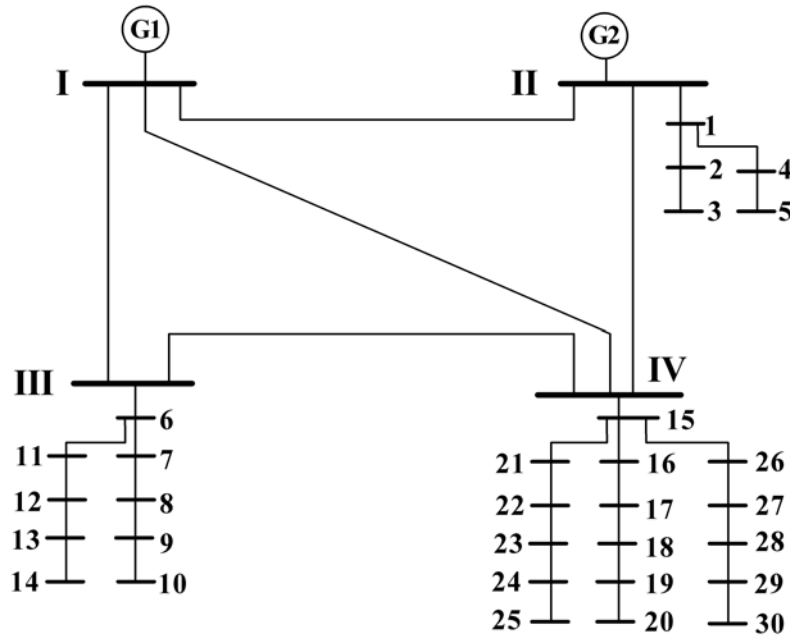


Figure 5.7: The 4-bus test system

The electricity spot price is calculated for different levels of total demand using the *economic dispatch* of generating units within the plants. From these individual spot prices, one can construct an aggregated price curve with respect to demand. In reality, such curves are in the form of a stepwise increasing function with each step reflecting the dispatch of an additional (and more expensive) unit to meet an additional demand. This paper, for simplicity, assumes a continuous estimation curve for spot price [84]:

$$\rho = a.(D_{\text{total}}/C_{\text{total}})^b + c \quad (5.17)$$

where  $D_{\text{total}}$  and  $C_{\text{total}}$  are total electricity demand and total generation capacity, respectively;  $a$ ,  $b$ ,  $c$ , are estimation coefficients determined from the given price data points. Using actual market data collected from the Australian National Electricity Market (NEM) (see [88] p. 99), a spot price estimation curve is derived, which is shown in Fig. 5.8, where  $a = 400$ ,  $b = 7$ ,  $c = 35$ , and  $C_{\text{total}} = 40$ .

The transmission network *EENS* is also estimated using (5.9). This estimation for the base load case is shown in Fig. 5.9, in that the analytical curve fits well with the corresponding data points calculated using the transmission reliability assessment procedure (as described above). This base-case *EENS* estimation results in the following (*DR*) *demand curve* to be used by the Transco in the *market-clearing* process:

$$p_2 = -7y_2 + 78 \quad (5.18)$$

$$p_3 = -9.4y_3 + 120 \quad (5.19)$$

$$p_4 = -8.5y_4 + 152 \quad (5.20)$$

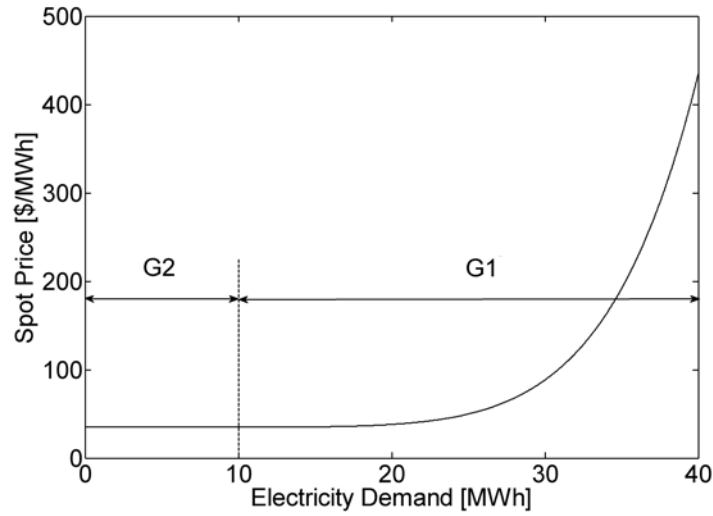


Figure 5.8: Spot price estimation curve

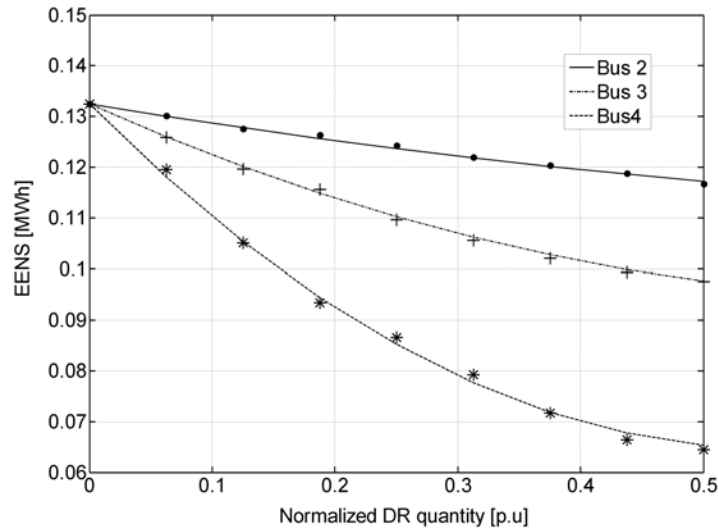


Figure 5.9: EENS estimation in the transmission network (Note: To simplify the illustration, each curve represents load reduction for providing DR at the corresponding bus subject to unchanged load at the other bus).

The customer-related data includes retail prices, electricity demand, and price elasticity. They are substituted in the *(DR) supply curve* (5.5). The electricity demand of individual customers is indicated above (through the feeder loads). The retail prices (in \$/MWh) and elasticity (no unit) are given in Tables 5.5 and 5.6, respectively. For simplicity, these prices are assumed to be fixed along the day and are (in short term) independent of the hourly levels of system loads. This is the case of the current Australian context.

It is also assumed that retail prices among different customers in the same distribution network can be different (See Table 5.5). This assumption is based on the fact that, due to

the “full retail contestability” that has been implemented in the real markets, customers are no longer “tied” to their physical locations in the network; they have a choice of supply contracts offered by different (competitive) Recos.

Table 5.5: Retail prices

Cons $l$	$\pi_l^{\text{int}}$	Cons $l$	$\pi_l^{\text{int}}$	Cons $l$	$\pi_l^{\text{int}}$	Cons $l$	$\pi_l^{\text{int}}$	Cons $l$	$\pi_l^{\text{int}}$	Cons $l$	$\pi_l^{\text{int}}$
1	200	6	200	11	170	16	170	21	150	26	130
2	200	7	200	12	170	17	150	22	150	27	130
3	200	8	200	13	170	18	150	23	150	28	130
4	200	9	170	14	170	19	150	24	130	29	130
5	200	10	170	15	170	20	150	25	130	30	130

Table 5.6: Customer elasticity

Cons $l$	$\epsilon_l$	Cons $l$	$\epsilon_l$	Cons $l$	$\epsilon_l$	Cons $l$	$\epsilon_l$	Cons $l$	$\epsilon_l$	Cons $l$	$\epsilon_l$
1	-0.11	6	-0.16	11	-0.21	16	-0.26	21	-0.31	26	-0.36
2	-0.12	7	-0.17	12	-0.22	17	-0.27	22	-0.32	27	-0.37
3	-0.13	8	-0.18	13	-0.23	18	-0.28	23	-0.33	28	-0.38
4	-0.14	9	-0.19	14	-0.24	19	-0.29	24	-0.34	29	-0.39
5	-0.15	10	-0.2	15	-0.25	20	-0.3	25	-0.35	30	-0.40

### 5.6.2 Evaluation results of the partial schemes

#### The Transco-based scheme

With the given demand and supply data, the market clearing model (5.11)-(5.12) is simulated using the non-linear programming tool GAMS/MINOS. The resultant DR quantities are then used for the next-step simulation—to calculate the out-of-market surpluses for Reco, Disco and Genco, respectively, by using (5.13)–(5.16).

The simulation here considers four different cases. Each corresponds to a certain level of the system load. Under these different loading levels, results of the market clearing and out-of-market calculation are given in Tables 5.7 and 5.8, respectively.

As expected, the social surplus is negative at 0.8 p.u. and 0.6 p.u. system loads. This is because the corresponding in-market total surpluses (45.8\$ and 17.2\$) are all outweighed by the out-of-market surpluses that are negative (−114.2\$ and −73.4\$). These results indicate that trading DR within the market, while benefiting every market participant (the Transco and customers), can be *conflicted* with some out-of-market parties as it causes financial losses incurred by them (e.g., Gencos).

It is interesting to observe that besides the Gencos, the Reco also suffers losses (−33.7\$ and −85.5\$) during these periods. This is because the spot prices at 0.8 p.u. and 0.6 p.u.

Table 5.7: Market clearing under the Transco-based scheme

System loading	DR quantity	DR payment	Customer surplus	Transco surplus	Total IM surplus
1.2 p.u.	2.4	166.8	83.4	14.4	97.8
1 p.u.	1.8	114.3	57.2	8.5	65.7
0.8 p.u.	1.34	74.8	37.4	7.6	45.8
0.6 p.u.	0.77	30.8	15.4	1.8	17.2

Table 5.8: Out-of-market surpluses under the Transco-based scheme

System loading	Disco surplus	Reco surplus	Genco loss	Total OOM surplus	<b>Social surplus</b>
1.2 p.u.	89.6	2298.3	2294.1	93.8	191.6
1 p.u.	68.7	453.8	513.9	8.6	74.3
0.8 p.u.	50.6	-33.7	130.5	-114.2	-69.2
0.6 p.u.	28.9	-85.5	16.8	-73.4	-56.2

are as low as 65\$/MWh (see Fig. 5.8), which is far less than the retail prices (see Table 5.5). Therefore, the scheduled DR, which reduces electricity demand, also reduces the profit for the Reco from buying bulk electricity at a low spot price and reselling it to the customers at higher prices.

During the other periods (corresponding to 1 p.u. and 1.2 p.u. system loads), the spot price is spiky, meaning that only a small reduction in the electricity demand results in a large reduction in the price. Unlike those causing losses in the 0.6 p.u. and 0.8 p.u. periods, DR in the form of load curtailments under spiky spot prices eventually brings extra profits to the Reco. Such profits are as much as 453.8\$ and 2298.3\$ in Table 5.8, respectively.

However, while the Reco gains higher profits, Gencos experience higher losses. This is because when DR is scheduled, the Genco profits are automatically *redistributed* to the Reco through the reduction of spot prices. For example, during the 1.2 p.u. period, as the electricity demand reduces from 36MWh to 33.6MWh, the spot price reduces significantly. As a result, DR surplus to the Reco is 2298.3\$, which mostly comes from the Genco (who are losing 2294.1\$).

The above observations are commonly called in microeconomics *externalities*, in which actions (DR scheduling) taken by some players (Transco and customers) directly affect the well-being of other players [75]. Due to these externalities, costs and benefits derived from DR are allocated *unfairly* among players, in which some players pay nothing but gain more benefit than others who has to pay. There may even be some players who suffer losses caused by conflicted capacity that is scheduled by other players. These issues related to externalities are substantiated by the above results.

Table 5.9: Market clearing under the Reco-based scheme

System loading	DR quantity	DR payment	Customer surplus	Reco surplus	Total IM surplus
1.2 p.u.	5.7	966.2	483.1	2779.2	3262.9
1 p.u.	2.6	243.6	121.8	319.6	441.4
0.8 p.u.	0.142	2.6	1.3	0.5	2.8
0.6 p.u.	0	0	0	0	0

Table 5.10: Out-of-market surpluses under the Reco-based scheme

System loading	Disco surplus	Transco surplus	Gencos loss	Total OOM surplus	<b>Social surplus</b>
1.2 p.u.	210.5	400.8	3790.3	-3179.2	83.7
1 p.u.	95.6	168.4	792.3	-528.3	-86.9
0.8 p.u.	5.6	8.5	17.1	-3	-0.2
0.6 p.u.	0	0	0	0	0

### The Reco-based scheme

To further illustrate the issues resulting from externalities, alternative DR-scheduling schemes including the Reco-based and the Disco-based are evaluated. However, since a Disco-based scheme is in general similar to the Transco-based, the study here focuses on assessing the Reco-based scheme only.

Under this scheme, the Reco has to pay for DR while both the Transco and Disco do not, rather they gain some reliability benefits for free. Since the Reco clears the DR market, it can derive the demand curve to be used for this market clearing. Such a curve would reflect a valuation in terms of how much this DR worth to the Reco. Mathematically, this curve is derived by taking partial derivatives of the DR benefit function (5.15), with respect to each quantity  $y_g$ . The obtained demand curve then is substituted to (5.11)-(5.12), to form a Reco-based market-clearing model. The evaluation results are shown in Tables 5.9 and 5.10, in comparison to the Transco-based scheme.

As can be seen, during periods of the 1.2 p.u. and 1 p.u. system loads, the Reco gains significant DR gross benefits ( $2779.2\$ + 966.2\$ = 3754.4\$$  and  $319.6\$ + 243.6\$ = 563.2\$$ , respectively). This is because when the Reco manages DR, it tends to increase this DR up to points (5.7MWh and 2.6MWh) where its gross benefits are optimal, which are higher than the benefits it gets (only 2298.3\$ and 453.8\$) when DR is managed by the Transco instead. However, Gencos at the same time suffer substantial losses since their profits are redistributed to the Reco through the spot price reduction. As a consequence, the Reco-based social surpluses during these hours are lower than those under the Transco scheme. Even the surplus at the 1 p.u. system load is negative ( $-86.9\$$ ).



During other periods, as electricity demand is relatively low (0.8 p.u. and 0.6 p.u.), the resultant spot price is relatively low (see Fig. 5.8). As discussed above, DR under this low price is not required because it will not bring any extra benefit to the Reco. Consequently, the Reco schedules very little or even no DR during the 0.6 p.u. and 0.8 p.u. loading periods. Although such scheduling causes no major loss to Gencos, it is conflicted with network operators as it reduces the reliability benefits compared with those under the Transco scheme given above.

Although the Transco-based scheme shows some advantages against the Reco-based, both schemes in our opinion are not efficient due to the common issue of externalities as observed in all the above results. Such externalities always lead to unfair situations where some players have to pay for DR that is freely used by other players, or where some players gain significant benefits while others lose money due to conflicted plans.

### 5.6.3 Evaluation results of the DRX scheme

Here we simulate the DRX market clearing scheme to see whether it can compensate for the above limitation of partial schemes (Transco-based and Reco-based). In general, this DRX scheme can be viewed as a generalization of the partial approach, in that the former incorporates costs and benefits of all involved parties (Discos, Recos, Transcos, electricity customers, but not Gencos) within the market clearing formulation [80].

A DRX can be either in the form of a pool-based model (developed in Chapter 3) or an agent-based model (i.e., in Chapter 4), depending on the underlying mechanism used to clear the market. These DRX models, however, have a common market clearing objective that is to maximize the total surplus derived from DR for all parties. For simplicity, only that objective is considered here to develop an assessment methodology applied to a DRX (in either type, pool-based or agent-based). This assessment can be defined as a best-case analysis, that is, analysing the outcome of a DRX in its best form. How to achieve such an outcome (i.e., using an appropriate market clearing mechanism) has been investigated extensively in previous chapters. Note also that the above evaluations of partial schemes are also based on their best-case scenarios.

The DRX market clearing objective is given by the following optimization [80]:

$$\max \left\{ \sum_{j \in \mathcal{J}} B_j - \sum_{i \in \mathcal{I}} C_i \right\} \quad (5.21)$$

$$y_{j,n} = \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}_i} u_{i,l}^{j,n} x_{i,l} \quad \forall j \in \mathcal{J}; n \in \mathcal{N}_j \quad (5.22)$$

where  $B_j$  is the gross benefit for each DR buyer  $j \in \mathcal{J}$  (the set of all buyers including Transco, Disco, Reco);  $C_i$  is the cost of load curtailment for producing DR by each seller

Table 5.11: In-market surpluses (\$) in the DRX

System loading	Reco surplus	Transco surplus	Disco surplus	Cus surplus	In-market surplus	Gen loss	<b>Social surplus</b>
1.2 p.u.	2438.8	193.7	143.2	595	3370.7	2976.5	394.2
1 p.u.	546.6	62.4	68.9	261.3	938.9	790.1	148.8
0.8 p.u.	25.5	9.15	3.45	51	89.1	50.1	39
0.6 p.u.	0	0	0	0	0	0	0

Table 5.12: In-market payments (\$) and DR quantities (MWh) in the DRX

System loading	DR quantity	Reco payment	Transco payment	Disco payment	Cus revenue
1.2 p.u.	3.5	369.5	276.5	543.4	1190
1 p.u.	2.1	109.1	261.5	152.1	522.7
0.8 p.u.	0.8	<b>-70.6</b>	99.6	72.9	102
0.6 p.u.	0	0	0	0	0

$i \in \mathcal{I}$  (the set of DR sellers, i.e., ESCOs on behalf of electricity customers). While  $C_i$  can be calculated by using (5.5),  $B_j$  relies on (5.10), (5.13)–(5.15). The difference between the gross benefit and the total cost is a market surplus, the value to be maximized. Constraint (5.22), on the other hand, refers to a balance between the demand for DR and its supply (Detail of this constraint can be found in previous chapters). In fact, the DRX model given by (5.21)–(5.22) is an mathematical extension of the above Transco-based market clearing model, (5.11)–(5.12).

The given DRX model has been simulated on GAMS/MINOS using the same input data with the Transco-based and Reco-based DR scheduling models. Results are given in Tables 5.11–5.12, in comparison with Tables 5.7–5.8 and Tables 5.9–5.10. As expected, these DRX results are significantly better than those of the Transco-based and Reco-based. The social surpluses (i.e., at most levels of system loading) are relatively high which clearly indicates the overall economic efficiency of DRX market clearing. Such an efficiency can be explained because there is no free rider (i.e., who pays nothing but still gains some DR benefit) in the DRX market. When all sellers (Transco, Reco, Disco) together pay for DR as a public good, the total payment (column 6 of Table 5.12) for load curtailing customers is much higher than would be the case of partial DR schemes given by Table 5.7 (i.e., in column 3) and Table 5.9 (i.e., in column 3). Such an increased compensation will be likely to motivate the customers to participate more actively in DR scheduling program than in the current practice [75, 80].

It is also observed from Table 5.11 that the social DR surpluses are non-negative in all cases (i.e., the smallest value of surplus are 0 for the case of 0.6 p.u. system load, when DR

is not scheduled due to its very low benefits). Such a no-negative outcome implies that there is no conflict of interest among Transco, Disco, Reco and electricity customers, which can be explained because their benefits are all considered in a DRX market. By contrast, not all costs and benefits of DR are incorporated within a partial market clearing scheme, i.e., Transco-based and Disco-based. This problem inevitably leads to a scheduling conflict among the involved parties and then a negative value of the social surplus, as has been demonstrated in Tables 5.8 and 5.10.

In all cases of system load, surpluses for the Reco are significantly higher than those of the Transco, Disco, and customers (see Table 5.11). This result could be explained by the externality in that scheduling DR in a DRX market affects the Gencos as an outsider. Here much of the Reco's benefit is transferred from the Gencos, via a reduction in electricity spot price. This externality resulting in a surplus transfer is not necessarily a limitation of the DRX proposal. It is, rather, considered a natural consequence of the competition between Recos and Gencos in an electricity trading market (i.e., in which ones win and the others lose). Unlike those in the Transco-based and Reco-based DR scheduling schemes, this competition is "healthy" in the sense that it keeps the value of DR positive, as has been demonstrated by Table 5.11, final column.

It is interesting to observe that DR payment made by the Reco during 0.8 p.u. period is negative ( $-70.6\$$  in Table 5.12), meaning that instead of paying an actual amount of money, the Reco gets compensated. This result can be explained by a loss incurred by the Reco due to DR scheduled in this period. In particular, the spot price at 0.8 p.u. system load is as low as  $65\$/MWh$  (see Fig. 5.8) that is far less than the retail price (see Table 5.5). Then the scheduled DR, which reduces electricity demand, also reduces the profit for the Reco from buying bulk electricity at low spot price and reselling it to the customers at higher retail prices. Due to this accidental loss, the Reco is compensated, for instance, by those DR beneficiaries (Transco and Disco). This compensation essentially resolves the conflict among players in DR scheduling. Indeed, it is a unique feature of DRX over the existing partial schemes.

Although these observations need further investigations, our numerical study has demonstrated the usefulness of the proposed framework for DR benefits evaluation. In particular, the framework considered a social view by taking into account cost and benefit for every stakeholder (i.e., Transcos, Discos, Recos, and electricity customers). In the light of comprehensive assessment, externality has been clearly observed. Additionally, the framework can analyse the benefits derived from different DR scheduling schemes such as Transco-based, Reco-based, and DRX. In this sense it can become a generalized tool for *testing* and *comparing* the effectiveness of various schemes to choose the best option (i.e., DRX in our study) for a liberalised power system.

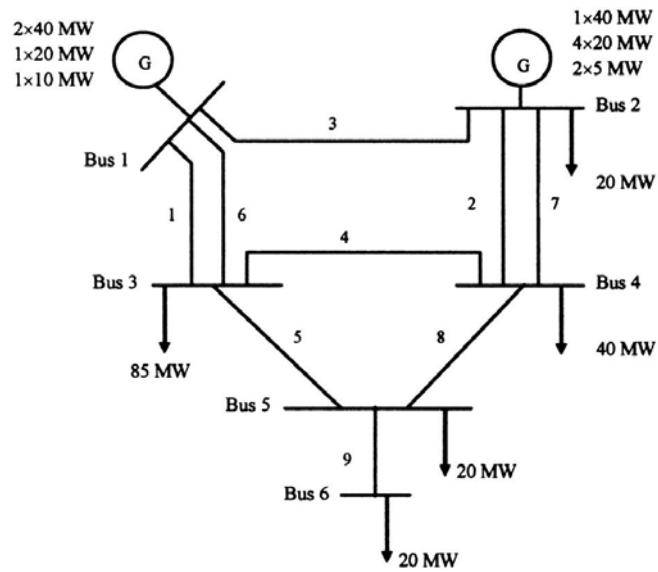


Figure 5.10: Transmission level of the RBTS [118]

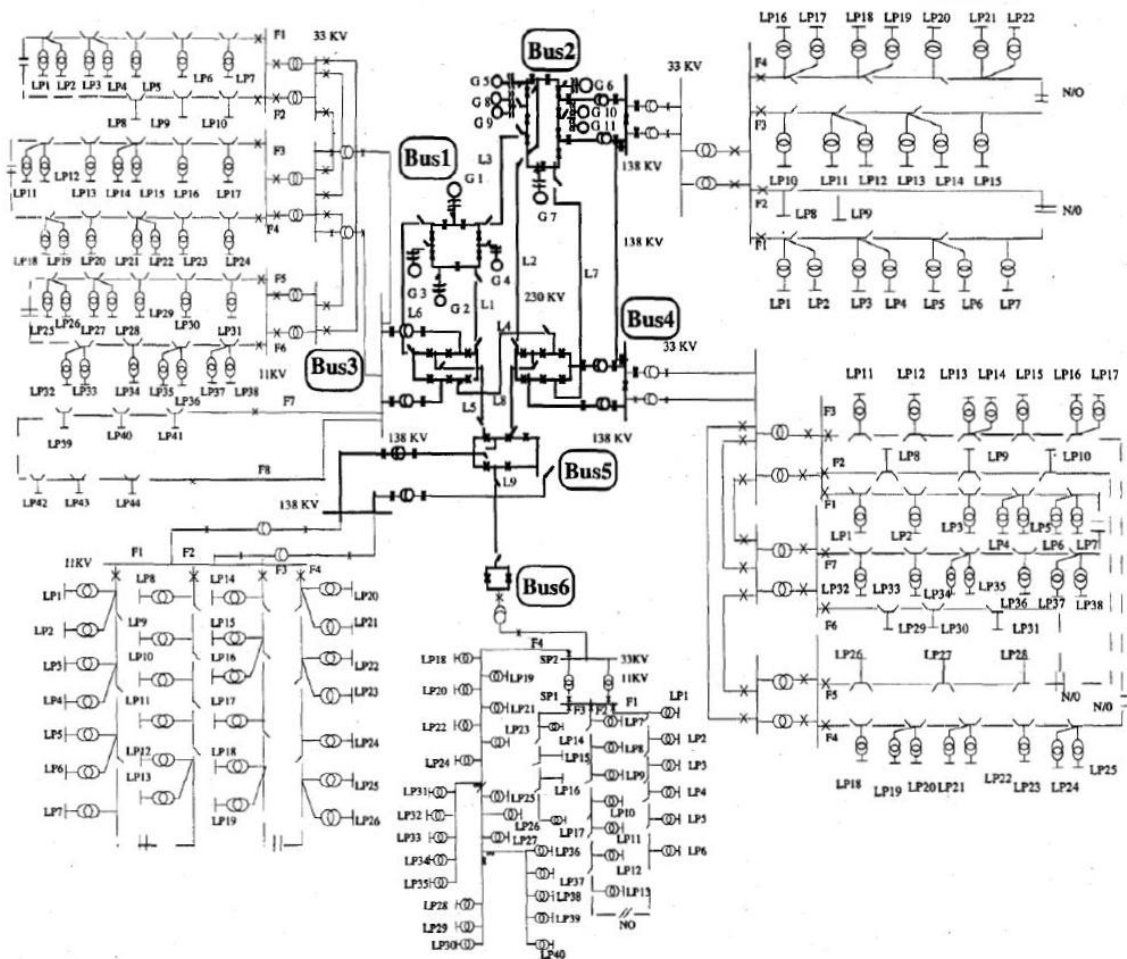


Figure 5.11: Full diagram of the RBTS [119]

## 5.7 RBTS case study

### 5.7.1 The RBTS

This section gives another case study to examine the scalability of the proposed assessment framework. This study also extends some problems identified above and thus provides a useful insight to DR costs and benefits. The study is performed on the Roy Billinton Test System (RBTS) [118].

As shown in Figs. 5.10 and 5.11, the system includes a 6-bus transmission network. Each bus is connected to a separate distribution network consisted of a substation and many radial feeders. The total base load of the RBTS is 185MW, and its power factor is assumed to be unity. The total generation capacity is 240MW. There are 170 load points (corresponding to 170 customers) at the distribution level. Further details of the RBTS (i.e., load flow data, reliability data) can be found in [118].

### 5.7.2 Estimating EENS

First we examine the *EENS* estimation using (5.9) that is central to the calculation of DR demand curves (5.10) and is based on a sensitivity analysis (SA). This estimation for the base case of 6-bus transmission network is shown in Fig. 5.12. Here each analytical function reflects the sensitivity of *EENS* to a load reduction at only one bus while loads at the other buses remain unchanged. As can be seen from the graph, these functions fit well the corresponding data points that are obtained via the network reliability assessment using a commercial software, DIGSILENT PowerFactory (<http://www.digsilent.com.au/>).

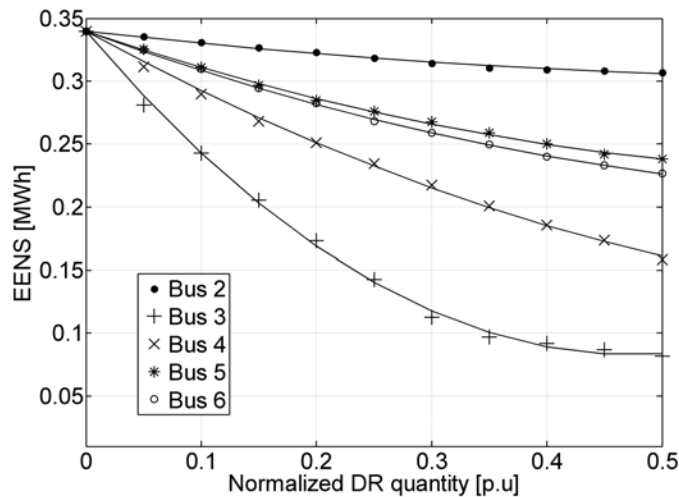


Figure 5.12: Sensitivity-based EENS estimation at the RBTS's transmission level

However, if loads at different buses are reduced simultaneously, the *EENS* estimation using the sensitivity function (5.9) will generally be inaccurate. This issue is explained

because, in a large-scale interconnected network, the impact on  $EENS$  of load reduction at one bus is closely *coupled* with the actual levels of loads at other neighbouring buses. For instance,  $EENS$  would be automatically lower if there are load reductions at other buses. Such a coupling effect however is not included in (5.9) and consequently becomes the main source of errors in  $EENS$  estimation.

To overcome the coupling issue in an interconnected power network, the sensitivity function (5.9) is extended as follows:

$$EENS = \sum_{n=1}^N (\alpha_n y_n^2 + \beta_n y_n) + \sum_{m,n=1}^N \theta_{m,n} y_m y_n + \gamma \quad (5.23)$$

where  $\theta_{m,n}$  is called mutual coefficient as a compensation of the self, locational coefficients  $\alpha_n$  and  $\beta_n$ . That is,  $\theta_{m,n}$  represents the coupling effect on  $EENS$  of the load reductions at every two buses ( $m$  and  $n$ ) in the network (Note that  $\theta_{m,n}$  and  $\theta_{n,m}$  are the same coefficient). Such a method is referred in this paper as ‘coupling sensitivity analysis (CSA)’—an extension of the above SA.

Both CSA and SA methods for  $EENS$  estimation are tested on the RBTS. Comparative results are included in Tables 5.13 and 5.14—each corresponding to a certain *feasible range* of load reductions (i.e., 0 – 0.1 p.u. and 0 – 0.5 p.u.). These results show the mean absolute percentage errors (MAPE) that is an average of absolute errors across all possible combinations of load reductions at different buses.

Table 5.13: MAPE of EENS estimation with 0 – 0.1 p.u. load reductions

Estimation methods	Roy Billinton Test System (RBTS)	
	Transmission level	Distribution level
SA	4.3%	2.4%
CSA	2.2%	1.9%

Table 5.14: MAPE of EENS estimation with 0 – 0.5 p.u. load reductions

Estimation methods	Roy Billinton Test System (RBTS)	
	Transmission level	Distribution level
SA	22.8%	6.5%
CSA	8.1%	6.2%

As expected, results for the CSA at transmission level are better than those of the SA. However, at the distribution level even the SA method can achieve very low MAPEs (i.e., 2.4% in Table 5.13 and 6.5% in Table 5.14). These good results are explained because of the *radial* structure of distribution networks (See those in Fig. 5.11). In particular, loads at different locations in the network are not interconnected, but instead are supported by

a common feeder having high power-transfer capability. In this sense, these distribution loads are mostly independent of each other and thus do not impose any significant coupling effects on the overall network performance (i.e., *EENS*). Without such effects, the SA method is equivalent to the CSA (See results in Tables 5.13 and 5.14).

The above results also suggest that some of the dimensional issues, associated with *EENS* estimation, come from the range of load reductions. For example, when these reductions are within a relatively small interval (such as 0 – 0.1 p.u. in Table 5.13), the coupling effect is still weak and therefore a simple SA method with a reasonable MAPE (4.3%) would be enough for the estimation. This is the case of the above small-scale study where the largest load reduction is only 2.4MWh/36MWh  $\simeq$  0.067 p.u. (See again Table 5.7). Note also that, in many real markets in Australia and the U.S., the maximum levels of load reductions currently do not exceed 5% (or 0.05 p.u.) [88]. On the other hand, if the reduction range is expanded (such as 0 – 0.5 p.u. in Table 5.14), the CSA method that is more complex than SA has to be used instead, particularly at the transmission level.

### 5.7.3 Spot price analysis

Although electricity spot price can be estimated using (5.17) which is a deterministic function, this estimation is not fully realistic due to the random nature of power supply. For example, during the operation of a power system, some generating units may fail to synchronize, consequently resulting in the *redispatch* of other units to meet the given power demand. Similarly, some parts in the network may be unexpectedly disconnected, which impose significant *constraints* on the other parts. In this case, generation must also be redispatched following another power flow “routine” that releases the constraints. This redispatching activity is undertaken using a certain amount of *reserve* that is the still-available, synchronized generation capacity. The use of this resource certainly alters the total generation cost and resultant spot price.

To incorporate these random factors of power supply within the spot price estimation, the deterministic function (5.17) can be extended as follows:

$$\rho = a.(D_{\text{total}}/C_{\text{total}})^b + c + \bar{s}(D_{\text{total}}) \quad (5.24)$$

where  $\bar{s}$  is a stochastic premium which is an amount added to the (original) price and given by the cost of generation redispatch during unforeseen outages, while the first two components of (5.24) represents the cost of *economic dispatch* without considering any technical, probabilistic constraints of the network [119]. Note also that the above small-scale study, for simplicity, utilized the actual price data that was collected from the real market (NEM), and more importantly, is comprised of both costs for economic dispatch (every 60 minutes) and redispatch (every 5 minutes) of the units [88]. The study here, on the other hand, will provide a useful insight into the behaviour of such prices.

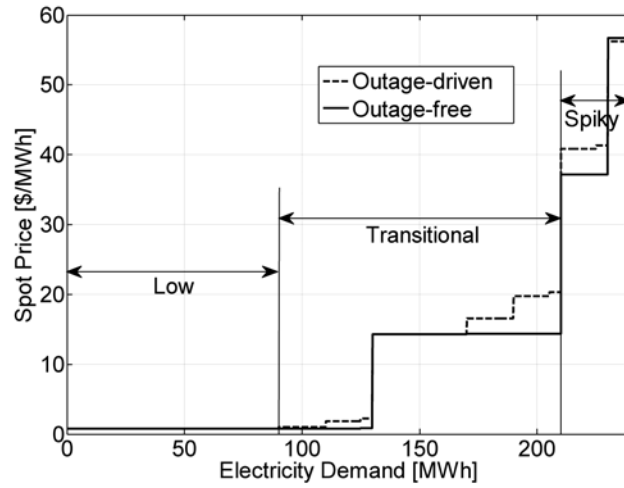


Figure 5.13: Effect of the outages on spot price

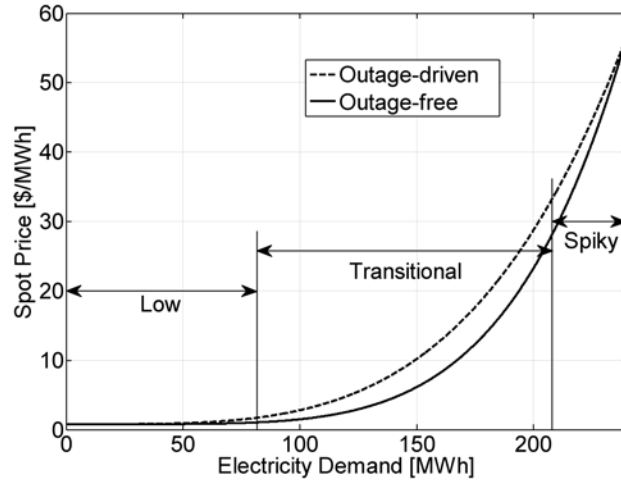


Figure 5.14: Illustration of the price estimation

The stochastic premium  $\bar{s}$  can be calculated together with  $EENS$  using a common network reliability assessment described above. That is, for each selected outage, all *online* generating units are redispatched to meet the given demand. If no feasible dispatching solution is found (or the solution is too expensive to be purchased), part of the demand will have to be curtailed [82]. The probability-weighted average of curtailments across all these outages is  $EENS$ , while that of the cost incurred by generation redispatch is considered  $\bar{s}$ . By regressing the  $\bar{s}$  values over different levels of demand, we obtain an analytical function  $\bar{s}(D_{total})$ . In this calculation, we assume that the level of reserve being used for generation redispatch has been pre-determined using a *fixed* criterion (i.e., capacity of the largest online unit in NEM [88]).

To perform spot price estimation using the network reliability analysis for a given reserve level, we develop a simple computer program embedded in the DigSILENT Pow-



erFactory software. This program employs the cost data of 11 generating units (7 hydro, 2 lignite, and 2 gas) of the RBTS [119]. Note that, in addition to the spot price estimation, this program calculates the *EENS* as mentioned above.

Fig. 5.13 presents simulation results for spot price with and without the consideration for outages. As can be seen from the graph, there are three pricing phases at different levels of electricity demand—low, transitional, and spiky. Within the first phase, the outage-free and outage-driven prices are the same. This is explained because the cost of generating units (i.e., hydro) being redispatched during outages is equal to the cost of other hydro units that have been used for dispatching before the outages.

Within the transitional phase, since more expensive units such as lignite and gas have to be scheduled, the resultant spot price become higher after the outages (See Fig. 5.13). However, price for the demand level between 130MWh and 170MWh remains unchanged because only the hydro and lignite units are used both before and after outages, while the expensive gas units still are not required here. Within the spiky pricing phase where the demand is reaching the generation limit (240MWh), there is not much capacity left for redispatching the units. Without a significant redispatch, the spot price does not change a lot after outages (see Fig. 5.13), but in turn, the demand is shed substantially to avoid a subsequent system blackout.

Fig. 5.14 gives approximation results for the above simulated spot price. MAPEs of this estimation are 16.8% for the outage-free curve and 12.4% for the outage-driven curve, respectively. This rather poor performance can be explained because the RBTS has only a few generating units which operate at significantly different ranges of costs (See Fig. 5.13). Such a *discrete* property makes the resulting spot price difficult for being fitted by a continuous mathematical function (for instance, (5.24)). This is, however, not the case in practice. For example, the real power system in NEM includes several hundred generating units whose costs represent a relatively continuous trend (See data given in [88]). Thus, estimating the resultant spot price in NEM using (5.24) will certainly be better than in the RBTS, as was examined by the previous case study.

#### 5.7.4 Clearing the DRX market

Here we examine the outcome of the DRX scheme given by (5.21)–(5.22), with DR cost and benefit calculations using (5.5), (5.10), and (5.13)–(5.16). In addition to the given reliability and generation data of the RBTS, customer data such as retail prices ( $\pi_l^{\text{int}}$ ) and elasticity ( $\epsilon_l$ ) must be specified. For simplicity, we assume that all customers are offered the same retail price (200\$/MWh) and have the same elasticity ( $-0.3$ ). Additionally, the spot price given in Fig. 5.14 is scaled up by 10 times, to be more constant with the current prices in NEM [88].

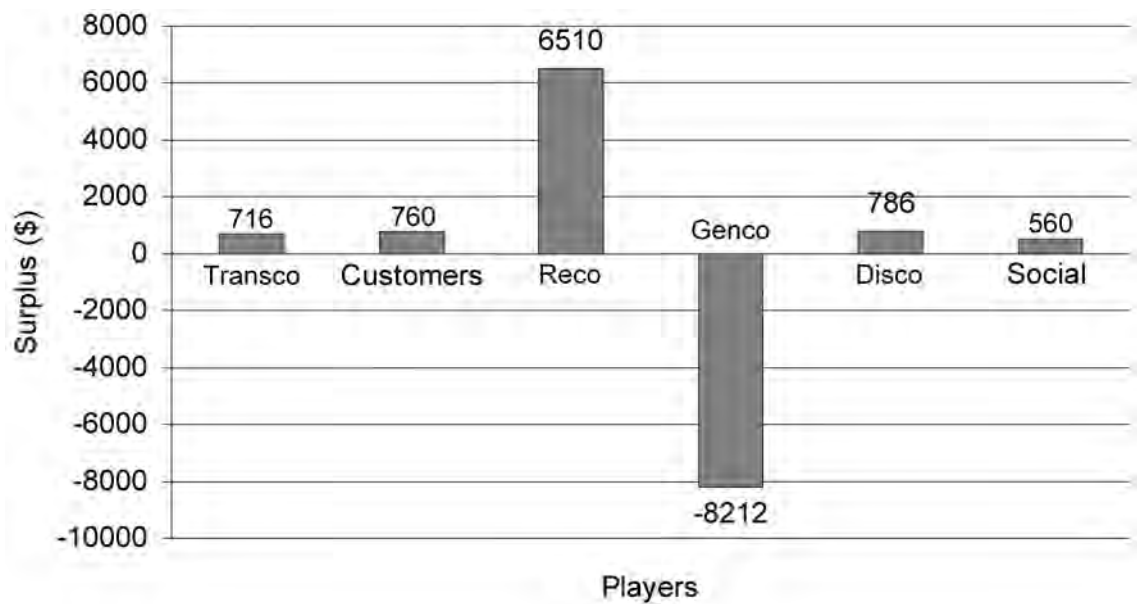


Figure 5.15: DR surpluses under the DRX market-clearing scheme

With these data, the DRX market clearing scheme is simulated and its results are shown in Fig. 5.15. As with the above small-scale study, externality is observed clearly here. The Gencos experience a substantial loss (\$8212) caused by the conflicted DR scheduled by other parties within the market. At the same time, the Reco gains a significant benefit (\$6510), most of which comes from the Gencos. Despite this externality, the social surplus is \$560 which is still compatible with the individual surpluses for Transco, Disco and the customers. This result shows the effectiveness of the proposed DRX scheme.

### 5.7.5 Computational issues

Despite the relatively small size of the RBTS, this case study is time-consuming because it entails using multiple softwares for different stages of the evaluation. First, the estimates of *EENS* (i.e., (5.23)) and spot price (i.e., (5.24)) were both carried out via DigSILENT PowerFactory. *Monte Carlo* simulation was used extensively for sampling and testing these estimates across all possible combinations of loads at different buses. Here each simulation performed a minimum of 500 trials and required on average a computation time of 30 min. The total time for all simulations, including those of the 6-bus transmission network and those of the 170-node distribution network in the RBTS, is around 100 min. However, in reality, these simulations are not done by a single body but by different responsible players such as the market operator, the Transco, and Discos *in parallel*. Consequently the actual computation time required here would be reduced down to 30 min only.

In this paper, no particular effort was made to reduce the above computing times—even the reliability assessment included in those simulations employed the full AC load–flow calculation (Newton–Raphson) rather than just the simplified DC method mentioned in the literature [116].

On the other hand, the time required for solving the Transco–based market–clearing model (5.11)–(5.12) using the programming tool GAMS is negligible (i.e., less than 1s), because of the simplicity of the model. In particular, this model is based on only the integration of the linear DR demand and supply curves (5.5) and (5.10), and therefore has a convex form that can be solved quickly using commercial tools. Note also that, even through the *EENS* estimation employed the CSA method (i.e., (5.23)) as an extension of the conventional SA (i.e., (5.9)), the resultant model (5.11)–(5.12) that is still convex consequently did not incur additional computation time.

All the simulations were performed in a Window–based PC with a 1.6–GHz chip and a 512–MB RAM.

## 5.8 Conclusion

This chapter developed a novel framework for assessing the financial surpluses of DR in a power system. Firstly, the framework analyses DR cost and benefit for each participant in a DR market, as well as those for the Gencos and Recos in an electricity trading market. Based on this local analysis, a global evaluation is performed, aiming to determine whether the optimized DR can produce a positive social surplus. If so, DR is dispatched into the system during the period under consideration.

The framework has been developed in a rigorous manner with a few justifiable assumptions. It employs only a limited number of input data easily obtained from real markets. For example, the retail prices can be collected from supply contracts offered by retailers to customers; the generation costs and equipment failure rates can be determined by the market and network operators. This advantage makes the framework readily applicable.

Regarding its applicability, the framework is a useful offline tool to analyse the economic plans of various categories of DR–involved players. It is also necessary for testing the effect of various issues associated with regulation and risk management in DR scheduling.

We performed extensive simulations to test the effectiveness of the proposed assessment framework. First, it was studied on a small system illustrating several interesting features of DR costs and benefits. The most notable feature is externality that causes substantial market distortions (i.e., leading to negative social surpluses in partial DR schemes). Another case study using the RBTS was given to examine the scalability of the proposed framework when dealing with larger power systems.

The major implication of our finding from the case studies is that the DRX market clearing scheme offers significant advantages over the conventional partial schemes. These advantages, which have been rigorously evaluated, include a mitigation of externality, a fair cost–benefit allocation (i.e., with the absence of free riders), and an improvement in social surplus derived from DR for all stakeholders.

## Chapter 6

# Conclusion and Future Studies

### 6.1 Thesis summary

In general, this thesis presented the development of a new and separate market for trading electricity demand response (DR) in a deregulated power system. This trade is comprehensive to the extent that it involves all consumers (through ESCos) as well as all electricity sector players including Transcos, Recos, and Discos. In our opinion, creating such a market is somewhat controversial and therefore entails significant discussion on its necessity and feasibility. Then the path we took throughout the thesis to analyse these critical aspects is summarised as follows.

In Chapter 1 we provided an introduction to the general research area of DR as well as its major scheduling challenges. In this direction, first we discussed some fundamental characteristics of electricity and its demand, including the storage difficulty and the demand inelasticity over time-varying prices. These characteristics entails a careful delivery of electricity from the power utilities to their customers, leading to the magnificent development of electric power supply systems. We reviewed the status of this development to date, with a particular focus on restructuring and deregulation issues. This restructuring, which introduces competition to the power system via the creation of wholesale and retail electricity markets, consequently results in the whole set of challenging problems associated with the task of maintaining a reliable and economical power supply. These challenges, namely network security management, market volatility and peak demand, can be overcome by introducing DR as a potential approach. In this regard, we estimated the financial benefit derived from DR capacity for the case of Australian national market under various resource utilization scenarios. It has been found that the current market scenario (i.e., with low DR utilization) offers very low incentives for DR-providing customers and that significant market benefits would be obtained if DR capacity is fully utilized. This essentially motivates the development of an effective DR scheduling scheme, forming the main

theme for the research carried out in this thesis. Finally, we overviewed our DR scheduling work by listing a number of research topics to be considered in subsequent chapters.

Chapter 2 was devoted to explain the necessity and the feasibility of demand response exchange (or shortly DRX) as a new and separate market in the restructured power system and as a comprehensive approach for scheduling/trading DR resource. The necessity can be explained by the fact that most existing works in this area, being classified as either Reco-based DR, Transco-based DR or Disco-based DR, constitutes only partial scheduling solutions because they consider the benefits for only a subset of participants in the power supply chain. From a technical point of view, this limitation may result in conflicts over how the same pool of DR capacity (i.e., customer load) is scheduled optimally while each player (Recos, Transco, and Discos) has their own plans for DR. From an economic perspective, partial DR scheduling approaches are inefficient because they cannot distribute cost and benefit fairly and flexibly among those participants. This situation is referred in microeconomics as “market failure” (i.e., fail to make an efficient allocation of the underlying resource). This problem raises the need for developing a comprehensive and fair DR scheduling scheme considering benefits across all players. A potential candidate for this development is DRX, where DR is treated as market product to be exchanged between two groups of market participants—buyers and sellers. Buyers, including Transcos, Discos, and Recos, request DR and pay for it. Sellers, including ESCOs on behalf of their electricity customers, supply DR as a source of income. The proposed DRX concept was found to be feasible as an informal generalization of those partial scheduling approaches. It is also considered in this thesis as an independent market for trading DR. However, in reality, DRX can be reconciled with other energy-related markets if required (i.e., for the purpose of co-optimizing the profit of delivering and utilizing all resources.)

In Chapter 3 we developed a pool-based market clearing model as a technical ground mechanism for DRX operation. In this model, buyers and sellers are required to submit demand and supply curves, respectively, reflecting their own marginal costs and benefits derived from a set of DR quantities. Based on this collected information, the DRXO (the market operator) clears the market by centrally maximizing the total benefit for all participants under several economic constraints aiming to ensure an effective market clearing outcome. These constraints include demand–supply balance and the obligatory payment of each DR buyer (Recos, Transcos and Discos). One of the central ideas in formulating this clearing model is to consider DR as public good—a special type of resource with each single unit utilized by multiple players. Due to this joint utilization, an assurance contract is developed as an effective tool to avoid the free-riding problem, that is, to encourage every DR beneficiary contribute voluntarily to the payment for the public good. This contract is embedded as an optimization constraint in the DRX clearing model. This developed model is then studied on a relatively small test system, revealing several interesting re-

sults for DRX. First, it was shown to be significantly better than conventional partial DR approaches including Reco-based, Transco-based, and Disco-based. Second, the fairness across all customers was observed, in which those curtailing more loads than others are compensated at a higher rate. Third, buyers are better off submitting bids reflecting their true benefits derived from DR. These results which are all consistent with microeconomic theory consequently substantiate the DRX pool-based clearing outcome.

In the next chapter we designed an agent-based mechanism, as an alternative of the pool-based, for clearing the DRX. The concept of economic agent was first introduced, resulting in a set of decentralized scheduling criteria. The Pareto efficiency concept was also presented, forming a ground in formulating the market clearing problem. This problem is then realised by a Walrasian auction scheme, in which participating agents (DR buyers and sellers) update their quantity bids in response to market prices adjusted by the DRXO. This process is repeated iteratively until the market equilibrium is adequately obtained at the point where the market outcome is Pareto optimal. One of the main results in this chapter was to prove both the existence and the uniqueness of this competitive equilibrium under some economic conditions (i.e., preference convexity) that are commonly adopted in economic modeling. Other results were to demonstrate the convergence of iterative price adjustment methods used by the DRXO in the Walrasian scheme. These are classical and Newton tâtonnements—both have advantages and limitations. Although the former is easy to implement, it may not converge to an equilibrium solution if the value of price adjustment factor ( $K$ ) is not suitably chosen (i.e., within its feasible range). On the other hand, the Newton tâtonnement method offers robust convergence, although in return it requires greater computational effort in estimating the Jacobian matrix online. This estimation can be performed using the finite-difference principle.

Last but not least, we proposed in Chapter 5 a comprehensive framework for assessing short-term financial costs and benefits derived from scheduling/trading DR. This framework has a hierarchical structure ranging from local cost-benefit up to global externality analyses. First, the financial value of DR for each market participant (customers, Recos, Discos, and Transcos) was quantified rigorously using certain valuation techniques such as customer utility characterization and electricity spot pricing, and also network reliability assessment. These quantified values were then fitted by appropriate analytical functions to be adopted for later evaluation stages. Once all local analyses have been done, a global evaluation is performed, aiming to examine the impact of externalities among participants, under market clearing conditions. The developed assessment framework was illustrated on both a small test system and the RBTS, showing its effectiveness with a reasonable accuracy in cost-benefit estimation. The proposed framework was also used to study the relative economic efficiencies of various DR scheduling/trading schemes including the DRX proposal and conventional partial approaches (Reco-based, Transco-based, and Reco-based).

Numerical results essentially demonstrated the significant advantages of the DRX, including a mitigation of externalities, a fair and flexible cost–benefit allocation due to an absence of free riders in the market, and a non-negligible improvement in social surplus derived from DR for all involved parties. These results are extremely important as they verify the public good scheduling analyses given in the previous chapters.

Overall, the objective of the research project reported in this thesis has been achieved. We did reviewed the existing works on investigating efficient DR scheduling schemes. Based on this review, we proposed a new DRX concept as an informal generalization of all those works. Then we designed and evaluated different market clearing mechanisms for DRX, using both analytical and numerical methods. We finally conclude that our DRX proposal, which represents a new and feasible approach for scheduling/trading DR, offers significant advantages over the conventional partial approaches.

## 6.2 Major contributions

The distinct contribution of this thesis to the main body of knowledge can be summarised as *to propose a new market for trading DR and to develop methodologies for designing and analysing such a market*. This innovation comprises the following points.

### 6.2.1 Constructing a public view of DR

The research project reported in this thesis was initiated from a simple but very interesting idea that DR can be viewed as a type of public good, in the sense that a given DR quantity is jointly utilized by multiple players. In microeconomics, public good is formally defined as good being non–rival and non–excludable. Non–rivalry means that consumption of the good by one individual does not reduce availability of the good for consumption by others; and non–excludability means that no one can be effectively excluded from using the good. Both of these properties are found to be approximately met by DR. For example, when a Transco buys a DR quantity from an individual customer, there are always a Disco and a Reco freely benefiting this quantity because their businesses still involve the customer, i.e., via network connection and retail contract. In addition to this non–rivalry, it is physically impossible to reject those third parties from utilizing the quantity, implicating the non–excludable property of DR.

The theory of public good often relates to the theory of market failure, and in this sense DR is not an exception. One can easily see the evidence of market failure in any existing DR scheduling/trading schemes as they fail to correctly value DR quantities provided by individual customers, leading to an inefficient allocation of this resource. Such a discovery was central to the preliminary analysis in our research project. In fact, we are not aware of any published work presenting this interesting idea.



### 6.2.2 The DRX concept

This concept is the first and most important proposal given in this thesis. It is considered an abstract solution to the problem of market failure associated with DR as a public good. In particular, those players providing DR (i.e., customers via ESCos) are placed on one side of the market and those demanding DR (i.e., Transcos, Discos, and Recos) are put on the other side. This arrangement facilitates significant market design and analysis to deal with the public good issue. In proposing this concept, we expected that a well-organized and competitive market for trading DR can thoroughly eliminate all relevant inefficiencies. Again, no such concept was found in the literature.

We should point out that the DRX concept itself is a natural implication following the market failure found in the existing DR schemes, and thus it should not be viewed as being controversial. While one may argue that implementing a new market which requires significant investment is not a readily feasible task, we believe that the long-term benefit created from that market would be sufficient to offset the investment cost. In this regard, our concept is not merely of academic interest but also a good solution to the problem of DR scheduling from a practical point of view.

### 6.2.3 Market clearing mechanisms

Since much has been written throughout this thesis about the development of these DRX mechanisms, here we discuss only their innovative aspects from an analytical perspective. The most interesting, and perhaps surprising, thing is that we were able to design a market with the presence of public good. To our knowledge, there is no such market well-developed for the competitive trading of such good (other than DR) in the current practice. What people often do is purchase those public goods (i.e., national defense, fresh air, common lands, rivers, etc.) under government control through the use of taxation.

The challenge in developing a competitive market for public good lies in its fundamental non-rivalry and non-excludibility that are also called non-linearity in engineering language. Due to these inherent characteristics, it is difficult to separate the allocation of public good between participants and then to correctly determine payment for/by each of them. This issue has been implicitly resolved in our DRX work using different approaches resulting in different types of market clearing mechanisms, namely pool-based and agent-based.

Based on this discussion, we suggest that our DRX proposal for a public goods market clearing scheme makes a good contribution to the field of microeconomics. We also believe that the analytical models developed in this thesis for competitive trading of DR can also be applied to trading other public goods, as long as they are not under government control. In fact, these models are generic in the sense that they involve multiple buyers, multiple sellers, and multiple products or quantities (i.e., an “exchange economy”). Note also that

such DRX models did not make any assumptions beyond those common in microeconomics, such as the preference convexity made in Chapter 4 for proving both the existence and the uniqueness of Walrasian market equilibrium.

#### **6.2.4 Comprehensive cost–benefit assessment**

The assessment work presented in Chapter 5 has significant implication as it establishes a good connection between the conventional power system analysis methods (i.e., reliability assessment, electricity spot pricing, etc.) and the DRX and other DR scheduling models. This explicit connection makes our proposal easily accessible for general power engineers, who might have only a little economic background and are not always convinced by theoretical economic arguments. In fact, the proposed cost–benefit assessment framework have brought our concept and models “down to earth” in the sense that it validates assumptions and approximations resulting from the DRX development.

In addition to supporting DRX, the framework is a useful offline tool to analyse economic benefits for various categories of DR-involved players. It is also necessary for testing the impact, on the DR scheduling outcome, of various market-related issues such as regulation, policy development, and risk management. The main advantage of the proposed framework is that the economic effects of DR on all market participants are considered together so a comprehensive estimate of the DR benefits can be obtained. We are not aware of any similar approach with ours, in the literature.

### **6.3 Suggestion for future research**

DRX is indeed a new research area with great opportunities for doing market design and analysis. Although most fundamental aspects have been adequately developed during this project, there remains some ideas yet to be considered due to time limit. Here we outline those ideas that may be worth studying as future research and development.

#### **6.3.1 Modeling of dynamic load recovery**

A dynamic feature of DR scheduling is the load recovery, the process by which electricity customers restore their consumption following load reduction [23]. This process is important as it can increase the cost of electricity supply during recovery hours when the retailers have to buy additional electricity from a volatile wholesale (spot) market and the network operators (i.e., Transcos and Discos) must deliver additional power using their stressed networks. Ideally, the value of DR capacity provided by customers should be calculated by taking into account both the benefits of load reductions and the costs associated with subsequent load recovery.

A comprehensive study of the load recovery effect on every participant (Recos, Transcos, Discos, and customers) in DRX markets should be the subject of further work in this area. We should point out that such a study can utilize our assessment framework given by Fig. 5.2. In particular, the players directly involved in the process of DR scheduling (i.e., via market clearing) are put in box I, while other participants that are not (but still either gain some free DR benefits or incur some losses) are put in box II. If all players were to participate in the DR scheduling process, box II would be removed. This case, however, is rare in current practice.

To account for the load recovery pattern across all participants, the assessment methodologies included in the proposed framework should be extended with: 1) details on the type of loads to be curtailed (i.e., HVAC application) and their recovery characteristics; and 2) inter-temporal stochastic effects of load recovery on both network reliability and spot price volatility along the scheduling horizon (i.e., one day).

### **6.3.2 DR price volatility**

Price volatility is an inherent characteristic of DR product being traded in a DRX. Once there is a perception in the market that there are sufficient DR supply to meet the demand, DR price will most likely drop quite dramatically—as similar to the electricity spot prices. There is also significant uncertainty in such DRXs because market participants never have perfect access to reliable information regarding current and future supply and demand for DR. This uncertainty essentially results in the price volatility.

Price volatility should also be the subject for future study in this area. Particular focus may be to mitigate this volatility by creating effectively on-going demand and having good market clearing strategies that continues to increase towards efficient market equilibrium. In this way, the conditions of demand and supply are kept relatively stable from time to time, resulting in non-volatile prices for DR.

Another solution to reduce price volatility is to augment the elasticity of demand and the elasticity of supply. For example, when demand is highly elastic, shifts in supply would have only little effect on market equilibrium price, although the market quantities change. When supply is highly elastic, shifts in demand will again have little impact on the market equilibrium price. This implicates the price stability (or non-volatility.)

### **6.3.3 Non-convexities**

The market design and analysis carried in this thesis, particularly Chapters 3 and 4, were largely based on convex optimization theory under the preference convexity assumptions (including cost convexity and benefit concavity). Although such mathematical assumptions are commonly used in economic modeling, it would be necessary to examine their validity by looking at the real market conditions. Experience in electricity markets suggests that

cost functions are not entirely convex and benefit curves not completely concave, which can be explained by the physical characteristics attached to these functions. For example, due to the ON–OFF operation of power generating units and electricity loads, the shapes of cost and benefit curves can be elbow or discontinuous at certain points, consequently resulting in their non–convexities in mathematical sense.

Study of the impact of non–convexities on DRX market clearing optimization outcome should be another topic for future work. This study may be presented in several directions. First, a proper convexification method can be utilized to “smoothen” the cost and benefit curves by which they are approximated by truly convex and concave functions, respectively. In this direction, data sensitivity analysis should be carried out to examine the effect of estimation errors on market outcome. Second, advanced optimization theory can be applied to solve the DRX market clearing problem in its original non–convex form. In particular, certain duality–based decomposition techniques should be able to convert that problem into an equivalent model (i.e., giving the same optimal results) which is convex and thus can be solved using commercial programming tools (i.e., GAMS) in polynomial time. This approach is promising since it has been (more or less successfully) applied for the case of wholesale electricity markets.

#### **6.3.4 Game–theoretic analysis**

Our DRX market equilibrium analysis was performed in Chapter 4 under the competitive conditions such that: 1) each participant is a price–taker (i.e., accepting the market price as it is); and 2) participants do not have private information of each other and thus cannot anticipate their bidding strategies. Again, experiences in electricity and other markets show that such conditions are not always satisfied, because there are certain players being able to exert market power and thus alter prices (for example, the 2002 California electricity market crisis); additionally some players can find ways to collect bidding information from others. Although these strategic behaviors can be alleviated introducing certain market policies and regulation (i.e., strong penalties to those strategic players), it is interesting to analyse their impact on DRX market outcome as a whole.

A major approach to this strategy analysis is game theory that explains the causes and consequences of conflict and cooperation between intelligent rational decision–makers (i.e., agents). As with microeconomics, game theory utilizes the notion of equilibria to model the outcome of the “game”. Among these, Nash equilibrium is the most widely–used concept, in which each player is assumed to know strategies of the others, and no player has anything to gain by changing his own strategy unilaterally. This Nash concept will be likely suitable for modeling the DRX market under strategic (rather than competitive) behaviour of the market agents (buyers and sellers.)

### **6.3.5 Long term impact assessment**

The work given in this thesis focused on short-term scheduling problems (i.e., hour-ahead). While this is important as being related to the daily operation of power systems, it would not be complete without considering the long-term impact of DR traded in a DRX. Such impact generally includes reducing the need of otherwise upgrading the physical power networks and the generation systems via significant investment. Such reductions can be quantified in financial terms, resulting in another monetary benefit of DR in addition to the short-term network reliability and market volatility mitigation benefits.

# Bibliography

- [1] D. Kirschen, “Demand-side view of electricity markets,” *IEEE Trans. Power Syst.*, vol. 18, no. 2, May 2003, , pp. 520-527.
- [2] R. J. Green and D. M. Newbery, “Competition in the British electricity spot market,” *J. Political Econ.*, vol. 100, no. 5, pp. 929-953, 1992.
- [3] B. Dallago and I. Iwasaki, *Corporate restructuring and governance in transition economies*, New York: Palgrave Macmillan, ISBN 9781403999351 (2007).
- [4] P. Quester, C. Neal, S. Pettigrew, M. Grimmer, T. Davis, and D. Hawkins, *Consumer Behaviors: Implications for Marketing Strategy*, McGraw-Hill, Sydney. ISBN 9780074716922 (2007).
- [5] R. H. Frank, *Microeconomics and behavior*, New York: McGraw-Hill/Irwin, ISBN 9780073375946 (2010).
- [6] D. Kirschen, and G. Strbac, *Fundamentals of Power System Economics*, New York: Wiley, ISBN 9780470845421, 2004.
- [7] American Physical Society (APS), “Challenges of Electricity Storage Technologies”, [Online], Available <http://www.aps.org/policy/reports/popa-reports/upload/Energy-2007-Report-ElectricityStorageReport.pdf>
- [8] K. Polanyi, C. M. Arensberg, and H. W. Pearson, *Trade and market in the early empires: economies in history and theory*, Glencoe, Ill: Free Press, ISBN (1957).
- [9] D. S. Kidwell, D. W. Blackwell, D. Whidbee, R. Peterson, *Financial Institutions, Markets, and Money*, Wiley Desktop Edition, ISBN 978-0-470-17161-5, (2009).
- [10] N. Lyndon, S. Joseph, M. Peter, *A Practitioner’s Guide to Corporate Restructuring*, City Financial Publishing, ISBN 978-1-905121-31-1, (2008)
- [11] <http://www.industry.nsw.gov.au/energy/market-reform/gas>
- [12] L. L. Lai, *Power System Restructuring and Deregulation*, John Wiley and Sons Ltd, ISBN 0 47149500 X, April, 2002.

- [13] C. L. Su, "Optimal demand-side participation in day-ahead electricity markets," Ph.D dissertation, Univ. Manchester, Manchester, U.K., 2007.
- [14] P. L. Joskow, "Why do we need electricity retailers? Or can you get it cheaper whole-sale?," Center for Energy and Environment Policy Research, 00-001 WP, January, 2000.
- [15] P. Hines, J. Apt, S. Talukdar, and H. Liao, "The frequency of large blackouts in the United States electrical transmission system: an empirical study," in *Proc. of the Second Carnegie Conference in Electric Power Systems: Monitoring, Sensing, Software and Its Valuation for the Changing Electric Power Industry*, 2006.
- [16] S. Blumsack, "How the free market rocked the grid," *IEEE Spectrum on Energy Policy*, Dec 2010.
- [17] New York Independent System Operator (ISO), "Interim report on the August 14, 2003 blackout," January 2004.
- [18] M. de Groot, "Managing residential energy consumption through universal energy services," in *Proc. of Green House 2009*, Perth, March 23-26, 2009.
- [19] J. L. Sweeney, *the California market crisis*, Stanford: Hoover Institution. ISBN 0-8179-2911-8, (2002).
- [20] C. Weare, *the California Electricity Crisis: Causes and Policy Options*. San Francisco: Public Policy Institute of California. ISBN 1-58213-064-7, (2003).
- [21] C. J. Cicchetti, J. A. Dubin, and C. M. Long, *the California Electricity Crisis: What, Why, And What's Next*, Kluwer Academic Pub, ISBN 9781402076923, (2004), Chapter 6.
- [22] U. S. Department of Energy, "Benefit of demand response in electricity market and recommendations for achieving them," Report to United States Congress Pursuant to Section 1252 of the Energy Policy Act of 2005, Feb. 2006.
- [23] G. Strbac, E. D. Farmer, and B. J. Cory, "Framework for the incorporation of demand-side in a competitive electricity market," in *Prof. of IEE Gener. Transm. Distrib.*, vol. 143, 1996.
- [24] D. Caves, K. Eakin, and A. Faruqui, "Mitigating price spikes in wholesale markets through market-based pricing in retail markets," *The Elect. J.*, vol. 13, no. 3, Apr. 2000, pp. 13-23.

- [25] D. T. Nguyen, "Demand response for domestic and small business consumers: A new challenge," in *Proc. IEEE PES T and D Conf. Expo.* 2010, Apr. 2010.
- [26] P. Cappers, C. Goldman, and D. Kathan, "Demand response in U.S. electricity markets: empirical evidences," *Ernest Orlando Lawrence Berkeley National Laboratory*, June 2009.
- [27] R. S. Fraser, "Demand side response in the national electricity market: Case studies," published by *Energy User Association of Australia (EUAA)*, April 2005.
- [28] G. Heffner, "Demand response valuation frameworks paper," *Ernest Orlando Lawrence Berkeley National Laboratory*, Feb. 2009, [Online]. Available: <http://drrc.lbl.gov/publications/demand-response-valuation-frameworks-paper>
- [29] Schweppe FC, Caramanis MC, Tabors RD, Bohn RE. *Spot pricing of electricity*, Boston, MA: Kluwer Ltd.; 1989.
- [30] J. Torriti, M. G. Hassan, M. Leach, "Demand response experience in Europe: Policies, programmes and implementation," *Energy*, Vol. 35, No. 4, April 2010, pp. 1575-1583.
- [31] R. Stewart, "Demand side management in support of the grid," in *Prof. of 2009 IEEE PES General Meeting*, 26-30 July 2009.
- [32] G. Strbac, "Demand side management: benefits and challenges," *Energy Policy*, 36 (2008), pp. 4419-4426.
- [33] M. Caramanis, "Investment decisions and long-term planning under electricity spot pricing," *IEEE Transactions on Power Apparatus and System*, PAS-101 Issue: 12, pp. 4640-4648 (1982).
- [34] M. Boiteux, "Peak-load pricing", *The Journal of Business*, Vol. 33, No. 2, pp. 157-179 (1960).
- [35] L. D. Kirsch, R. L. Sullivan, T. A. Flaim, J. J. Hipius, and M. Krantz, "Developing marginal costs for real-time pricing," *IEEE Trans. Power Syst*, Vol. 3, No. 3, pp. 1133-1138.
- [36] B. Hobbs, and S. Nelson, "A nonlinear bi-level model for analysis of electric utility demand-side planning issues," *Annals of Operations Research*, Vol. 34, No. 1, pp. 255-274.
- [37] J. Sheen, C. Chen, and J. Yang, "time-of-use pricing for load management Programs in Taiwan Power Company," *IEEE Trans. Power Syst*, Vol. 9, No. 1, pp. 388-396.



- [38] C. S. Chen, and J. T. Leu, "Interruptible load control for Taiwan power company" *IEEE Trans. Power Syst*, Vol. 5, No. 2, pp. 460-465.
- [39] K. H. Ng, and G. B. Sheblé, "Direct load control-a profit-based load management using linear programming," *IEEE Trans. Power Syst*, Vol. 13, no. 2, pp. 688-694.
- [40] M. Fahrioglu, and F. L. Alvarado, "Designing Incentive Compatible Contracts for Effective Demand Management," *IEEE Trans. Power Syst*, Vol. 15, no. 4, pp. 1255-1260.
- [41] H. -p. Chao, S. S. Oren, S. A. Smith, and R. B. Wilson, "Multilevel Demand Subscription Pricing for Electric Power," *Energy Economics*, Vol. 8, No. 4, pp. 199-217.
- [42] C.-L. Su, and D. Kirschen, "Quantifying the effect of demand response on electricity markets," *IEEE Trans. Power Syst.*, vol. 24, no. 3, Aug. 2009, pp. 1199-1207.
- [43] H. S. Oh, and R. J. Thomas, "Demand-side bidding agents: modeling and simulation," *IEEE Trans. Power Syst.*, vol. 24, no. 3, Aug. 2008, pp. 1050-1056.
- [44] H. Fraser, "The importance of an active demand side on the electricity industry," *The Elec. J*, vol. 14, no. 9, Nov. 2001, pp. 52-73.
- [45] A. B. Philpott, E. Petersen, "Optimizing demand-side bids in day-ahead electricity markets," *IEEE Trans. Power Syst*, Vol. 21, No. 2, May 2006, pp. 488-498.
- [46] S. Borenstein, and J. Bushnell, "An empirical analysis of the potential for market power in California's electricity industry", *The Journal of Industrial Economics*, Vol. 47, No. 3, pp. 285-323.
- [47] E. Amundsen, A. Nesse and S. Tjøtta, "Deregulation of the Nordic power market and environmental policy," *Energy Economics*, Vol. 21, No. 5, pp. 417-434.
- [48] B. H. Bakken, and K. Uhlen, "Market-based AGC with online bidding of regulating services," in *Proc. IEEE PES Summer Meeting*, 2001, Vol. 2, pp. 848-853.
- [49] D. Soler, P. Frias, T. Gomez, and C. A. Platero, "Calculation of the elastic demand curve of a day-ahead secondary reserve market," *IEEE Trans. Power Syst.*, Vol. 25, No. 2, May 2010.
- [50] J. Wang, N. E. Redondo, and F. D. Galiana, "Demand-side reserve offers in joint energy/reserve electricity markets," *IEEE Trans. Power Syst.*, vol. 18, no. 4, Nov. 2003, pp. 1300-1306.

- [51] Y. T. Tan and D. S. Kirschen, "Co-optimization of energy and reserve in electricity markets with demand-side participation in reserve services," in *Proc. 2006 IEEE Power Syst. Conf. Expo.*, Atlanta, Georgia, Nov. 2006, pp. 1182-1189.
- [52] National Grid Company Settlement Limited, "Introduction to the Pool Rules," April 1993.
- [53] G. Strbac, D. Kirschen, "Assessing the competitiveness of demand-side bidding," *IEEE Trans. Power Syst.*, Vol. 14, No. 1, February 1999, pp. 120-125.
- [54] E. Karangelos, and F. Bouffard, "Towards full integration of demand-side resources in joint energy/reserve electricity market," *IEEE Trans. Power Syst.* (submitted).
- [55] T. -F. Lee, M. -Y. Cho, Y. -C. Hsiao, P. -J. Chao, and F. -M. Fang, "Optimization and implementation of a load control scheduler using relaxed dynamic programming for large air conditioner loads," *IEEE Trans. Power Syst.*, Vol. 23, No. 2, May 2008, pp. 691-702.
- [56] A. Gomes, C. H. Antunes, and A. G. Martins, "A multiple objective evolutionary approach for the design and selection of load control strategies," *IEEE Trans. Power Syst.*, Vol. 19, No. 2, May 2004, pp. 1173-1180.
- [57] A. Gomes, C. H. Antunes, and A. G. Martins, "A multiple objective approach to direct load control using an interactive evolutionary algorithm," *IEEE Trans. Power Syst.*, Vol. 22, No. 3, Aug 2007, pp. 1004-1011.
- [58] C. M. Chu, and T. L. Jong, "A novel direct air-conditioning load control method," *IEEE Trans. Power Syst.*, Vol. 23, No. 3, Aug 2008, pp. 1356-1363.
- [59] M. A. Pedrasa, T. D. Spooner, and I. F. MacGill, "Scheduling of demand-side resources using binary particle swarm optimization," *IEEE Trans. Power Syst.*, Vol. 24, No. 3, Aug 2009, pp. 1173-1181.
- [60] A. H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. L. Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. Smart Grid*, Vol. 1, No. 3, Dec 2010, pp. 320-331.
- [61] Y. Guo, J. Li, and G. James, "Evolutionary optimization of distributed energy resources," in *Proc. of Australian Joint Conference on Artificial Intelligence (AI 2005)*, Sydney, Australia, LNCS 3809, pp. 1086-1091, December 2005.

- [62] M. A. Pedrasa, T. D. Spooner, and I. F. MacGill, "Coordinated scheduling of residential distributed energy resources to optimize smart home energy services," *IEEE Trans. Smart Grid*, Vol. 1, No. 2, September 2010, pp. 134-143.
- [63] D. T. Nguyen, M. Negnevitsky, and M. de Groot, "Demand response in the retail market: Benefits and challenges," in *Proc. AUPEC09*, 27-30 September, pp. 1-6.
- [64] M. Negnevitsky, D. T. Nguyen, and M. de Groot, "Novel Business Models for Demand Response Exchange," in *Proc. IEEE PES General Meeting 2010*, pp. 1-6.
- [65] R. Billinton, R. N. Allan, *Reliability evaluation of power systems*, Plenum Press, New York and London, 1996.
- [66] A. Boogert, and D. Dupont, "When supply meets demand: the case of hourly spot electricity prices," *IEEE Trans. Power Syst.*, Vol. 23, No. 2, May 2008, pp. 389-398.
- [67] F. P. Ramsey, "A contribution to the theory of taxation," *Econ. J.*, vol. 37, no. 145, Mar. 1927, pp. 47-61.
- [68] Electric Power Research Institute (EPRI), Report to NIST on the Smart Grid Interoperability Standards Roadmap, Contract No. SB1341-09-CN-0031-Deliverable 7, June 17, 2009.
- [69] <http://www.consumerenergyreport.com/smart-grid/>
- [70] The Western Australian Council of Social Service Incorporated (WACOSS), "Electricity retail market review issues paper," Jan 2008.
- [71] <http://www.abc.net.au/news/stories/2011/01/04/3105828.htm>
- [72] Southern California Edison, "Aggregator demand response programs," 2010.
- [73] R. W. Melicher, E. A. Norton, *Introduction to finance: markets, investments, and financial management*, John Wiley and Sons Ltd (2008).
- [74] Y. Zhang, W. Chen, and J. Black, "Anomaly Detection in Premise Energy Consumption Data," in *Proc. IEEE PES General Meeting 2011*, July 2011.
- [75] A. Mas-Colell, and M. D. Whinston, J. R. Green, *Microeconomic theory*, Oxford University, Press (1995).
- [76] M. A. Ortega-Vazquez, D. Kirschen, "Optimizing the spinning reserve requirements using a cost/benefit analysis," *IEEE Trans. Power Syst.*, vol. 22, no. 1, Feb. 2007, pp. 24-33.

- [77] E. R. Brubaker, "Free ride, free revelation, or golden rule?," *Journal of Law and Economics*, Vol. 18, No. 1, Apr. 1975, pp. 147-161.
- [78] M. Bagnoli, and B. L. Lipman, "Provision of public goods: fully implementing the core through private contributions," *The Review of Economic Studies*, Vol. 56, No. 4, Oct. 1989, pp. 583-601.
- [79] A. Tabarrok, "The private provision of public goods via dominant assurance contract," *Public Choice*, March 1996, pp. 345-362.
- [80] D. T. Nguyen, M. Negnevitsky, and M. de Groot, "Pool-based Demand Response Exchange—Concept and Modeling," *IEEE Trans. Power Syst.*, vol. 26, no. 3, August 2011, pp. 1677-1685.
- [81] M. Fahrioglu, and F. L. Alvarado, "Using utility information to calibrate consumer demand management behaviour models," *IEEE Trans. Power Syst.*, Vol. 16, No. 2, May 2001, pp. 317-321.
- [82] D. Kirschen, "Power system security," *Power Eng. J.*, Vol. 16, October 2002, pp. 241-248.
- [83] R. Billinton, and R. N. Allan, *Reliability evaluation of power systems*, Plenum Press, New York and London, 1996.
- [84] H. Bessembinder and M. L. Lemmon, "Equilibrium pricing and optimal hedging in electricity forward markets," *J. Fin.*, vol. 57, no. 3, 2002, pp. 1347-1382.
- [85] M. Parvania, and M. F. Firuzabad, "Demand Response Scheduling by Stochastic SCUC," *IEEE Trans. Smart Grid.*, Vol. 1, No. 1, June 2010, pp. 89-98.
- [86] A. A. S. Algarni, and K. Bhattacharya, "A generic operations framework for discos in retail electricity market," *IEEE Trans. Power Syst.*, Vol. 24, No. 1, Feb 2009, pp. 356-367.
- [87] U.S. Department of Energy, "Demand response in the West: lessons for states and provinces," Jun. 2004.
- [88] Australian Department of Resources, Energy, and Tourism, "Review of energy-related financial markets electricity trading," Nov. 2006.
- [89] C. L. Su, D. Kirschen, "Quantifying the effects of demand response in electricity markets," *IEEE Trans. Power Syst.*, vol. 24, no. 3, Aug. 2009, pp. 1199-1207.

- [90] K. H. Ng, G. B. Sheble, "Direct load control—a profit-based load management using linear programming," *IEEE Trans. Power Syst.*, Vol. 13, No. 2, pp. 688-695, May 1998.
- [91] S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, Prentice Hall, 2009.
- [92] M. Negnevitsky, "Computational Intelligence Applications to Crisis Management in Power Systems", *International Journal of Automation and Control*, Vol. 2 No. 3, 2008, pp. 247-273.
- [93] A. L. Motto and F. D. Galiana, "Equilibrium of Auction Markets With Unit Commitment: The Need for Augmented Pricing," *IEEE Trans. Power Syst.*, vol. 17, Aug. 2002, pp. 798-805.
- [94] R. Axelrod, *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*, Princeton: Princeton University Press, 1997.
- [95] D. T. Nguyen, M. Negnevitsky, and M. de Groot, "Walrasian market clearing for demand response exchange," to appear in *IEEE Trans. Power Syst.*, TPWRS-00232-2011.
- [96] S. M. Amin, and B. F. Wollenberg, "Towards a Smart Grid", *IEEE Power and Energy Magazine*, september-october, 2005.
- [97] N. Furniss, "The Practical Significance of Decentralization", *The Journal of Politics*, Vol. 36, No. 4, 2009, pp. 958-982 .
- [98] A. L. Motto, F. D. Galiana, A. J. Conejo, and M. Huneault, "On Walrasian equilibrium for pool-based electricity markets," *IEEE Trans. Power Syst.*, Vol. 17, No. 3, Aug 2002, pp. 774-781.
- [99] S. Boyd, and L. Vandenberghe, *Convex Optimization*, Cambridge Univerity Press (2004).
- [100] P. Samuelson, *Foundations of Economic Analysis*, Harvard University, Press, (1947).
- [101] A. J. Wood and B. F. Wollenberg, *Power Generation, Operation, and Control*, John Wiley Sons, (1996).
- [102] K. J. Arrow, G. Debreu, "Existence of an Equilibrium for a Competitive Economy," *Econometrica*, Vol. 22, No. 3, Jul 1954, pp. 265-290.
- [103] H. Scarf, "Some examples of global instability of the competitive equilibrium," *International Journal of Economic Review*, Vol. 1, No. 3, Sep 1960, pp. 157-172.

- [104] C. T. Kelly, *Iterative methods for linear and nonlinear equations*, Society for Industrial and Applied Mathematics, Philadelphia (1995).
- [105] D. C. Parkes, *Iterative combinatorial auctions achieving economic and computational efficiency*, PhD thesis, University of Pennsylvania, 2001.
- [106] D. Fudenberg and J. Tirole, *Game Theory*, Cambridge, MA: MIT Press, 1991.
- [107] A. L. Motto, *Price schedules coordination for electricity pool markets*, PhD thesis, McGill University, 2001.
- [108] F. A. William, *Numerical Methods for Partial Differential Equations*, Academic Press, New York, 1977.
- [109] E. J. Mishan, and E. Quah, *Cost/benefit analysis*, 5th Edition, Taylor and Francis e-Library, London and New York, 2007.
- [110] <http://www.aph.gov.au/library/pubs/climatechange/governance/domestic/national/mandatory.htm>
- [111] L. R. Ireland, *Project Management*, McGraw-Hill Professional, (2006).
- [112] A. Ertas and J. Jones, *The Engineering Design Process*, 2nd ed, New York, N.Y., John Wiley and Sons, Inc, (1996).
- [113] Paul A. Samuelson, “The Pure Theory of Public Expenditure”, *Review of Economics and Statistics*, Vol. 36, No. 4, pp. 387-389, 1954.
- [114] A. J. Conejo, J. M. Morales, and L. Baringo, “Real-time demand response model,” *IEEE Trans. Smart Grid*, vol. 1, no. 3, Dec. 2010, pp. 236-242.
- [115] F. Bouffard, F. D. Galiana, and A. J. Conejo, “Market clearing with stochastic security—Part I: Formulation,” *IEEE Trans. on Power Sys.*, Vol. 20, No. 4, November 2005, page 1823.
- [116] R. Billinton, and R. N. Allan, *Reliability assessment of electric power systems using Monte Carlo methods*, Plenum Press, New York and London, 1994.
- [117] M. A. Ortega-Vazquez “Optimizing the spinning reserve requirement”, PhD Thesis, University of Manchester, (2006).
- [118] R. Billinton, and Y. Cui, “Adequacy assessment of composite power systems with FACTS devices using a dc load flow method”, *Electric Power Components and Systems*, vol. 33, no. 10, Oct 2005.

- [119] R. Billinton, and S. Jonnavithula, "A test system for teaching overall power system reliability assessment," *IEEE Trans. Power Syst.*, Vol. 11, No. 4, Nov. 1996, pp. 1670-1676.